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Modeling Household Interactions in Daily Activity Generation

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Modeling Household Interactions in Daily Activity Generation

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Modeling Household Interactions in Daily Activity Generation

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This dissertation seeks to contribute to the area of activity-based travel-demand modeling by examining the impacts of inter-personal interactions within a household on the daily activity participation choices of individuals. A comprehensive analysis framework is developed for modeling the weekday, in-home and out-of-home activity participation choices of adults in active, nuclear-family households, as an outcome of individual and household needs, desires, opportunities, and spatio-temporal and resource constraints. The analysis framework explicitly captures several kinds of interactions between the household heads, such as sharing of household-maintenance tasks, engagement in joint activities, and the trade-offs between independent and joint discretionary activity participation. In addition to these inter-personal interactions, the intra-personal trade-offs among the different activity participation choices are also accommodated in this framework.

The empirical model system in this study comprise the following three components: (1) a seemingly unrelated regressions model for in-home maintenance activity generation, (2) a joint mixed-logit hazard-duration model for out-of-home maintenance activity generation, and (3) a multiple discrete-continuous (binary logit - linear regression) model system for discretionary activity generation. These models are estimated using data from the 2000 Bay Area Travel Survey.

This research also develops a micro-simulation framework for using the model system for predicting disaggregate, household-level, activity-participation choices. Thus, the modeling framework developed in this dissertation, can be embedded as an enhanced "activity-generation module" within a comprehensive micro-simulation-based activity-travel forecasting system. Finally, an application of the developed micro-simulation framework for the analysis of the impacts of policy actions on the inter-dependent daily activity participation choices of adults is presented.

In the overall, this research is envisioned as a very important first step in the development of an operational, activity-based, travel-demand forecasting system that comprehensively accommodates various intra-personal and inter-personal linkages in daily activity-travel choices.

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Chapter 1 Introduction

1.1 General Background

Transportation planners are interested in forecasting travel demand in order to design and operate efficient transportation systems. Data on current travel patterns of people are used to develop travel-demand models, which, in turn, are used to predict future travel characteristics under alternate scenarios of population socio-demographics, land-use patterns, transportation system characteristics, and institutional policy actions. Forecasting travel demand under these different kinds of scenarios requires that the underlying travel-demand models incorporate realistic representations of individual and household activity-travel decision-making behavior (Bhat and Lawton, 2000).

The conventional "trip-based" or "four-step" approach to travel-demand modeling, however, has been found to be lacking in such a realistic representation of travel behavior (Bhat and Koppelman, 1999a). The concerns about using this four-step process for travel-demand modeling and transportation planning have particularly become acute in the last couple of decades, and especially after the 1991 Intermodal Surface Transportation Efficiency Act (ISTEA) which emphasized the need for accurate analysis of transportation improvements on congestion, travel, and land use. At the same time, the last couple of decades have also seen very significant developments in the "activity-based" travel-demand modeling approach, which seeks to address the shortcomings of the traditional methodology.

This chapter first compares the trip-based and activity-based approaches to travel demand modeling and identifies why activity-based models are better suited to meet the current day transportation planning and air-quality modeling requirements. The subsequent section discusses the importance of household interactions in shaping individuals' daily activity-travel patterns and highlights the need to accommodate these interactions explicitly in activity-based travel models. Next, the overall objectives of this research are presented. The chapter ends with a description of the structure of this dissertation.

1.2 Trip-Based *versus* Activity-Based Methods of Travel Modeling

The fundamental difference between the trip-based and the activity-based approaches is that the latter approach explicitly treats travel as a derived demand. The trip-based approach models travel "as though demanded in its own right" (page 6, Jones, *et al.*, 1983). The activity-based approach, however, recognizes that travel is derived from a more fundamental need to participate in activities and, therefore, emphasizes the modeling of activity-participation characteristics as a precursor step to determining travel demand (Jones *et al.*, 1990). Further, the trip-based approach adopts a very simplified representation of the daily travel pattern in which an individual's day is treated as a *collection of independent trips*. Therefore, this method clearly ignores the spatial, temporal, and modal linkages among the different trips made by a person. In addition, the trip-based approach also does not recognize the inter-dependencies among the travel decisions of household members. The activity-based methodology, on the other hand, adopts a holistic view of the complex phenomenon of travel by focusing on the *overall sequence of activity-travel participation* of all household members over a day or longer periods of time. Therefore, this method explicitly considers the linkages among the different activity-travel decisions of an individual and also the linkages among the decisions of household members. Finally, the trip-based modeling approach, which comprises four sequential models of trip generation, trip distribution, mode choice, and network assignment, has often been described as "statistically oriented" and as a set of "*ad hoc* empirical specifications lacking in behavioral basis" (Bhat and Koppelman, 1999a; Kurani and Lee Gosselin, 1997). The modeling procedure does not reflect how travel-related decisions are actually made. For example, it is not reasonable to expect that individuals actually choose the number of home-based and non-home-based trips to be made during the day, as is assumed by the trip-generation models.

In contrast, the activity-based approach is more "behaviorally-oriented" with its focus on modeling inter-dependent activity-participation decisions (for example, decisions on frequency of participation in different activity types, the sequence in which the activity episodes are undertaken, duration, time-of-day, and location of participation of each activity episode, and mode of travel from one episode to another). Unlike the four sequential models in the trip-based approach, the activity-based approach often comprises a suite of several inter-dependent models capturing the linkages among the different activity-travel choices.

The above-mentioned differences between the trip-based and activity-based approaches in the representation and modeling of travel behavior have substantial implications in terms of their applicability to represent travel behavior and their use for the transportation planning requirements of today. These implications are discussed below, in the next four sections.

1.2.1 Representing Travel Behavior

The appropriateness of the trip-based representation of daily travel behavior is questionable on two counts. First, with multiple-stop tours becoming more prevalent (Gordon *et al.*, 1988), the linkages among the different trips made by a person during the day are becoming stronger. As a consequence, an approach that ignores these linkages is not a realistic representation of travel patterns. Second, with phenomenal advances in the field of telecommunications and consumer electronics, it is now increasingly possible to substitute several out-of-home activities with equivalent in-home activities (for example, telecommuting instead of the conventional work commute, watching movies in-home on a home-theatre system as opposed to going out to the cinema theatre, and e-shopping). The conventional methodology that focuses only on trips cannot accommodate impacts of substitutions between out-of-home and in-home activities on the overall travel patterns of people. The activity-based approach, which focuses on both in-home and out-of-home activity-participation choices, is therefore better suited to describe travel behavior in an era of in-home technologies.

1.2.2 Addressing Current Transportation Planning Needs

The focus of transportation planning has been shifting from long-term capital-intensive infrastructure development projects to short-term transportation control measures (TCMs) such as HOV lanes, congestion pricing, and peak spreading (see, for example, Bhat and Lawton, 2000). While the trip-based approach was adequate for forecasting aggregate traffic levels for prioritizing infrastructure development projects, it is not well suited for evaluating the impacts of TCM policy actions. For example, empirical research by Bhat and Singh (2000) indicate that the four-step process can over-predict the success of transit improvement strategies, since this four-step methodology ignores the linkages among the different trips of an individual. Further, impacts of several other TCM actions cannot be evaluated within the trip-based modeling framework (Stopher, 1993; Kitamura, 1997). In contrast, the activity-based approaches can capture the behavioral responses of people to policy actions and therefore are better suited to realistically predict the impact of TCM policy actions on the overall travel patterns for the entire day or longer periods (Kitamura *et al.*, 1997; Shiftan and Suhrbeir, 2002; Bhat and Singh, 2000).

1.2.3 Addressing the Needs of New Transportation Operations and Control Capabilities

With advances in the Intelligent Transportation System (ITS) technologies, it is now increasingly possible to detect and react to current traffic conditions and proactively influence the travel behavior of people in order to maximize the use of available resources. The design and operation of such dynamic control systems (for example, time-varying congestion-pricing schemes) requires predictions of travel at a detailed temporal resolution. The four-step process is rather limited in its treatment of time (Pas, 1998), and the time-of-day when the trips are being made is often determined only at an aggregate level of “peak” versus “off-peak” periods. The activity-based approaches, however, describe activity-travel patterns of individuals in terms of their overall time-use decisions (Bhat and Koppelman, 1999b). Therefore, these methods can provide the required detailed temporal characteristics of activity-travel patterns.

1.2.4 Addressing Environmental Concerns

Transportation modelers are also increasingly concerned about air-quality due to mobile source emissions, especially after the Clean Air Act Amendments (CAAA) of 1990. Modeling mobile source emissions requires a high level of spatial and temporal resolution in the movement of vehicles. These resolutions are often, well beyond the precision of the current travel-demand forecasting models (Stopher, 1993). Further, modeling air-quality also requires information on soak-time, *i.e.*, the duration for which the vehicle has been at rest before use. Since the conventional approach does not consider the temporal linkages between successive trips, this information is not available, limiting the use of the trip-based approach to air-quality modeling. Consequently, current travel-demand models have to be “mechanically” linked with air-quality models (Shiftan and Suhrbier, 2002). The activity-based approach, with its focus on both activity and travel duration and time-of-day, is better suited for the development of integrated travel-demand and air-quality models.

In summary, the trip-based travel-demand forecasting methods that were developed in the 1950s and 1960s to address problems very different and much simpler from that of today’s and with minimal computing capabilities (Lee-Gosselin and Pas, 1996) are not appropriate for representing travel behavior or for application to current transportation planning and air-quality modeling requirements. At the same time, the activity-based approach to travel modeling has emerged as not only a means to enrich the science of travel behavior with its behavioral orientation, but also an important tool to address very real transportation planning and travel/emissions forecasting needs that are not adequately met with the current state of practice. The reader will note that we have used the terms “trip-based approach” and “four-step approach” interchangeably. There have also been trip-based approaches that extend the four-step process to accommodate specific elements of the activity-based approach by addressing facets such as trip chaining. Nonetheless, even such enhanced trip-based approaches are inadequate compared to activity-based methods in comprehensively addressing the requirements of travel demand modelers today. Above all, the activity-based approach also offers “a fresh and significantly different perspective from which to view transport problems and generate policy options” (Jones, 1983).

1.3 Accommodating Daily Household Interactions in Activity-Based Travel-Demand Models

The increasing need for behaviorally oriented models that are sensitive to transportation policy measures has motivated substantial interest in the development and refinement of activity-based methods for travel-demand modeling. The main emphasis of such methods has been modeling individuals’ complete daily activity schedule. Individuals, however, do not make decisions about activity/travel participation in isolation (Golob, 1997). Rather, the household members interact in many ways, and consequently, their activity-travel patterns are inter-dependent. Within the context of modeling short-term activity-travel demand, four types of household interactions are of importance. These are (1) Sharing of household maintenance responsibilities by family members, (2) Joint engagement of household members in activities and travel, (3) Facilitation of activity participation of household members with restricted mobility by undertaking pick-up and drop-off trips, and (4) Sharing the use of common household vehicles.

Accommodating inter-personal inter-dependencies in travel-demand models is necessary for the realistic representations of travel behavior for several reasons. First, the roles played by the household heads today are more complex than conventional task specializations in which the men undertook out-of-home work for wages and the women were responsible for household chores. Between 1950 and 1990 the proportion of adult women working increased from 32% to 54.8%, whereas the proportion of adult men working decreased from 85.1% to 73.6% (Sarmiento, 1996) Also, men spent 5.2 more hours on housework in 1985 than they did in 1965, whereas women spent 7.5 fewer hours on housework in 1985 than they did in 1965 (Sarmiento, 1996). These statistics indicate a trend towards increased sharing of the wage-earning responsibilities and household maintenance tasks. Consequently, the linkages in the activity-travel patterns of the household heads are likely to be stronger today than they have been in the past. <u>Second</u>, the attributes of serve-passenger trips are often dictated by the characteristics of the activity participation of the person being "served". For example, the time-of-day of the pick-up/drop-off trips undertaken by parents to escort children to and from school are determined by the school hours of the child. Hence, serve-passenger travel decisions of an individual cannot be determined in isolation from the activity participation decisions of the person being served. <u>Finally</u>, individual-level models that ignore inter-personal interactions cannot determine characteristics of the activities and travel undertaken jointly by household members. Such joint activities constitute an important component of the overall activity participation behavior of household members.

As a consequence of its ability to realistically represent travel behavior, activity-based models that incorporate household interactions may be expected to better reflect the responses of households to changes in land-use and travel characteristics as well as changes in demographic characteristics. On the other hand, failure to recognize travel as a consequence of complex household interactions may result in erroneous or biased predictions of changes in travel patterns due to transportation control measures. For example, a policy action, such as congestion pricing during the peak-period, that directly impacts the activity-travel pattern of the worker in the household could also have impacts on the activity participation behavior of the non-working member in the household (who may not be directly affected by the policy) due to household task reallocations (Scott and Kanaroglou, 2002). Individual-level models cannot predict such secondary effects. Vovsha *et al.* (2003) identify that modeling of the decision to undertake joint travel by the household members is essential for realistic evaluation of policies such as High-Occupancy-Vehicle (HOV) lanes. Further, an understanding of the linkages in the activity-travel patterns of household members can also inform the formulation of transportation policy actions and urban design towards achieving goals of improving the overall quality of life of the people (Kitamura *et al.*, 1997).

1.4 Research Objectives

The recognition of linkages among the travel patterns of household members is one of the fundamental aspects of the activity-based paradigm (Pas, 1985; Jones *et al.*, 1990). However, much of the work in activity modeling over the past couple of decades has focused on modeling individual activity patterns in isolation, with relatively limited research on the complex inter-dependencies that exist among the activity-travel patterns of all individuals in a household. In surveys on the state-of-the art in activity-based modeling and time-use research, Bhat and Koppelman (1999b), Bhat and Lawton (2000) and Vovsha *et al.* (2004a) identify modeling household interactions as a critical area of research in activity-based travel modeling.

The goal of this research is to contribute to the area of activity-based analysis by examining the impact of inter-personal interactions on the daily activity participation choices of household heads in dual-adult households. Thus, this study represents a very important first step towards developing activity-based travel-demand models that comprehensively accommodate the effects of various inter-personal interactions in shaping the overall activity-travel patterns of individuals. The objectives of this study are as follows:

1. Develop a framework for modeling the weekday in-home and out-of-home activity participation choices of adults in nuclear family households, as an outcome of individual and household needs, desires, opportunities, and

constraints. This overall framework explicitly captures several kinds of interactions between the household heads: (a) sharing of household-maintenance tasks, (b) joint engagement in discretionary activities, (c) the trade-offs made by individuals between independent and joint discretionary activity participation, and (d) the impact of several observed (for example, automobile availability) and unobserved (for example, common life style choices, availability of opportunities for in-home activity participation, altruism, etc.) factors on the relative activity participation choices of the spouses. In addition to these inter-personal interactions, the intra-personal trade-offs among the different activity participation choices are also accommodated in this framework.

2. Develop appropriate econometric structures that capture the desired interaction effects for modeling the different activity-generation choices of the spouses. Specifically, this dissertation contributes methodologically by developing flexible econometric structures and identifying the estimation procedures for modeling discrete-continuous choices.
3. Estimate models using data from the Bay-Area Travel Survey, 2000 (BATS 2000) and examine the impact of factors such as household and personal demographics, automobile ownership, household location characteristics, employment-related characteristics, urban land-use patterns, and transportation system characteristics on the daily activity generation.
4. Develop a methodology for using the proposed model system in forecasting household activity-generation choices within a micro-simulation based-framework, which can then be embedded as an enhanced "activity generation module" within a comprehensive micro-simulation based activity-travel forecasting system such as the Comprehensive Econometric Micro-simulator of Daily Activity-travel Patterns (CEMDAP, Bhat *et al.*, 2004a).
5. Demonstrate the application of the model system for the evaluation of travel demand management (TDM) policy actions. Specifically, the intent here is to

highlight the advantages of activity-based models that accommodate household-interactions over the more conventional individual-level models.

1.5 Structure of the Dissertation

The rest of this dissertation is organized as follows. Chapter 2 presents a review of the literature examining household interactions in activity participation and time use choices. Chapter 3 develops the mathematical modeling framework for our analysis of household interactions, identifies the different model components within the framework, and formulates the econometric structure associated with each component. Chapter 4 presents the detailed mathematical structure of each of the model components identified in Chapter 3 and also describes the estimation procedures. Chapter 5 identifies the sources of data used in this analysis, describes the sample preparation procedure and presents several descriptive statistics on the sample. Chapters 6, 7, and 8 present the empirical model results for in-home maintenance activity generation, out-of-home maintenance activity generation, and discretionary activity generation, respectively. Chapter 9 describes the methodology for using the model system for disaggregate choice predictions, and also presents the TDM evaluation simulations. Chapter 10 summarizes the important contributions of this research and identifies areas of further research

Chapter 2 Literature Review

2.1 Introduction

The field of activity-based travel-demand modeling has seen phenomenal interest in the past couple of decades. Several researchers have explored different facets of the problem of characterizing and modeling activity and travel patterns. Some of these studies have examined one or more aspects of activity participation behavior (such as activity generation, activity sequencing, duration of activity episodes, location, and time-of-day) in great detail. Other studies have adopted a wider focus to develop comprehensive activity-based travel demand modeling systems. The following studies provide snap-shots of the state-of-the art in activity-based travel-demand modeling at different points in time over the past couple of decades: Damm (1983), Pas (1985), Kitamura (1988), Jones, *et al.* (1990), Axhausen and Garling (1992), Kitamura (1997), Khurani and Lee-Gosselin (1997), and Bhat and Koppelman (1999a). Vovsha *et al.* (2004a) discuss the progress made by metropolitan planning agencies in the Unites States in incorporating activity-based approaches in regional travel demand models. Despite this substantial overall interest in activity-based modeling, the issue of accommodating household interdependencies has not received adequate attention in activity-based modeling studies until much recently. However, certain aspects of household interactions such as task allocation have long been an area of research in fields such as sociology and economics, although the intent of these studies is not necessarily towards the determination of travel demand.

This chapter seeks to position our research within the overall context of earlier research in the area of interpersonal interactions in activity participation choices of household members. Towards that end, this chapter is organized in the following manner: Section 2.2 reviews theories of household interactions and time-use from various disciplines of study. Section 2.3 describes empirical efforts in the field of transportation aimed at accommodating inter-personal interactions in activity- and travel-demand models. Section 2.4 provides a review of the methodological advances in specification and estimation of advanced choice models. Finally, Section 2.5 presents a summary and identifies the key contributions of this research.

2.2 Theories of Household Interactions in Activity-Generation and Time-Use

The intent of this section is to provide a brief overview of theories describing household labor division and time-use behavior. The studies reviewed in this section are broadly classified into (1) sociological theories of division of family work, (2) economic theory of household labor allocation and (3) integrated "socio-economic" theories of time use. Each of these is respectively presented in Sections 2.2.1, Section 2.2.2, and Section 2.2.3.

2.2.1 Sociological Theories on Division of Family Work

Sociologists are interested in understanding the overall functioning of the family and the roles and responsibilities of its members. Many studies in this field have investigated how the husbands and wives divide household tasks (child care, cooking, cleaning, shopping, paying bills, etc.) between themselves. Blair and Lichter (1991) identify three prominent theories that describe the division of household responsibilities (or family work) between the household heads. These are (1) the gender-role theory, (2) the time availability theory, and (3) the resource or power theory. Each of these theories is described briefly here.

The *gender role theory* hypothesizes that men and women quite naturally have different functional roles to play in the household based on the biological differences between the two sexes. Further, women are also trained early in their lives to assume traditional "feminine" roles (Thomson and Walker, 1989). Consequently, the more the traditional sex-roles are ingrained in one or more of the family members, the greater is the wife's responsibility for family tasks (Hiller, 1984). Research indicates a trend towards sharing of household tasks by married couples (Ross *et al*., 1983), suggesting gender-based roles may not be descriptive of task allocation in contemporary society. However, Blair and Lichter (1991) argue that such a transition is not complete and there is evidence for continued gender-based task allocations.

The *time-availability* theory hypothesizes that division of household chores simply reflects the time availability of the different family members for undertaking household chores (see for example, Kamo, 1988 and Hiller, 1984). The time availability is often dictated by the employment status of the household members and their work durations. The member with more time can undertake household chores with greater ease than those operating under time pressures and, consequently, assume a greater share of household tasks. Hiller (1984) argues that time pressures alone cannot possibly be a powerful predictor of division of family tasks as households in which the wife is also employed are not found to have an equitable division of tasks between the husband and wife, as would be expected based on this theory.

The r*esource theory* or the *power theory* (Cromwell and Olson, 1975) hypothesizes that household task allocation is influenced by the bargaining power wielded by the different household members. This power of household members is derived by their relative contribution of resources and is often characterized by socio-economic factors like education, employment status, income, etc. (see for example, Kiker and Ng, 1990). A powerful family member (*i.e.,* one that contributes more resources) not only has a greater influence on the behavior of other members but also is less likely to be influenced by others. Townsend (1987) identified the main deficiencies of the resource theory as (1) lack of consideration of the overall welfare of the household in task allocation decisions, (2) problems with the definition and measurement of resources, and (3) conflicting empirical evidence of the effect of resources on power.

In summary, there are at least three sociological theories seeking to explain the division of household tasks between the husband and wife. There is no clear evidence favoring any one theory over the others. At the same time, it appears quite possible that the family task-allocation is actually a consequence of *all* the different reasons put forth by these theories (*i.e.,* gender roles, time constraints, and bargaining power or influence).

2.2.2 Economic Theory of Household Labor Allocation

In contrast to sociologists who have predominantly focused only on division of household chores between spouses, economists have examined the allocation of household labor to both household chores and the external market (*i.e.,* working in return for wages).

In the economic theory of household labor allocation*,* households are treated as both consumers as well as producers. Households produce "basic commodities" by combining goods purchased in an external market and time investments by household members. The conversion of these inputs into commodities is described via "household production functions", which forms a central idea in the economic theory (Mincer, 1962; Becker, 1965; Becker, 1981; Gramm, 1975; Gronau, 1973). The relative worth of the different bundles of basic commodities to the household is described using a utility function. Within this framework, the economic theory hypothesizes that rational households, when operating under monetary and time budget constraints, that limit the availability of inputs for household production, seek to maximize household's utility (*i.e.*, do what is best for the household as a whole). Consequently this theory implies that members invest time in external market (work) and home production (household tasks) based on their relative productivities in these two sectors. Wage rate is often used to describe productivity in market work while efficiency in producing home-goods describes productivity at home. In the overall, the economic theory implies considerable task specializations of one member in the external market and the other in home-productions to achieve efficiency.

A key limitation of the economic theory is that it assumes task allocation is purely dictated by efficiency considerations and ignores the role of factors such as social norms, habits, and interpersonal “bargaining”. Further, the economic theory also assumes a sexual bias in task specializations with the men investing time in the external market and women investing time in home-production (Townsend, 1987). Finally, Pollack and Wachter (1975) argue that “the household production function approach requires strong assumptions about the household’s technology, in particular constant returns to scale and the absence of joint production” and therefore can be a satisfactory model only under very special cases.

2.2.3 Integrated “Socio-Economic” Theories of Time Use

The sociological theories focus on the division of household tasks and capture the “human nature” of the interactions (*i.e.,* bargaining and power, impact of the social norms, personal ideologies, etc.). The economic theory, on the other hand, examines the time allocation between external markets and home, and captures the desire for achieving efficiency by making the best use of available monetary and time resources. Thus, each of these theories presents a partial description of the overall household time-use behavior. This section describes efforts to integrate ideas from sociology and economics to develop theories for describing inter-personal interactions in the time-use decisions of household members. Geerken and Gove (1983) are credited with undertaking the first steps in developing an integrated socio-economic theory based on imperfect utility maximization, although they did not explicitly formulate the structure of the underlying utility functions and constraints.

Townsend (1987) developed the first comprehensive theory of household task allocation within a utility maximizing framework. This theory examines the allocation of time by household members in the market-sector, home-production, and leisure. Townsend postulated that household members allocate time so as to maximize household utility, which in turn is a function of utility derived by each of the household members. The power of an individual determines the relative contribution of his/her utility to the overall household utility. The individual’s utility was defined as a function of the individual’s consumption, satisfaction derived from activity participation, and altruistic benefits from the activity participation of other household members. The household's attempt to maximize its utility is constrained by monetary and time budget constraints. Thus, this theory explicitly recognizes the impact of both social and economic factors in time use of household members.

Townsend's theory, however, does not account for shared utility derived by household members by undertaking activities jointly. Gliebe and Koppelman (2002) developed a theory of time-use that explicitly accommodates joint activity participation decisions of household heads in maintenance and leisure activities. The authors identify that joint activities are motivated by several considerations, including efficiency, altruism, and companionship, and develop a utility-theoretic representation for describing the time-use decisions in two adult households. As in the case of Townsend's model, the household's utility is assumed to be composed of individual's utilities weighted by the relative power of the different individuals. The individual's utility is defined as a function of individual's consumption, satisfaction derived from activity participation, altruistic benefits from the activity participation of other household members, and companionship derived from joint activity participation with the other household head. It follows from their model formulation that the proportion of daily time allocated to any activity by an individual is the proportion of daily utility derived from participating in that activity. Further, by explicitly imposing the constraint that the amount of joint time invested by one member in any activity is equal to the amount of joint time invested by the other member, Gliebe and Koppelman have derived the analytical model structure, which takes the proportional-shares form.

Studies undertaken by Zhang and colleagues [Zhang *et al.* (2002, 2004a), Zhang and Fujiwara (2004) and Zhang *et al.* (2004b)] have also focused on developing a household utility-maximizing model of daily time use accommodating both independent and joint activity participation decisions of household heads in two adult households. As in the case of Gliebe and Koppelman's theory, research by these authors also explicitly recognizes that the daily activity choices are a consequence of a group decision mechanism of the household members. Further, these studies have examined two different types of structures for the household utility functions, the multi-linear and the iso-elastic functions, each representing a different kind of group decision-making mechanism. As opposed Gliebe and Koppleman's model, which focused on modeling the fraction of daily time invested in each activity type, the approach presented by Zhang and colleagues models time-use in terms of the total duration invested in each activity type. The analytical model structure takes the form of a system of seemingly unrelated regression equations.

2.3 Empirical Studies in Transportation

The empirical research efforts examining the impact of household interactions in shaping the daily activity-travel patterns of individuals may be broadly classified into the following three categories based on the methodology used for analysis: (1) continuous choice modeling approaches, (2) discrete-choice and shares modeling approaches, and (3) exploratory analyses. Each of these is discussed in detail here.

2.3.1 Continuous Choice Modeling Approaches

The continuous choice modeling approaches for the analysis of household interactions involve the joint modeling of multiple continuous-choice variables (for example, the activity durations of the husband and the wife). This joint estimation is accomplished either using the structural equations modeling (SEM) approach or the seemingly unrelated regressions (SUR) modeling approach.

2.3.1.1 Structural equations modeling (SEM) approaches

Structural equations models allow the simultaneous estimation of multiple equations with specified causal linkages among the different dependent variables. Most of the studies employing the SEM methodology have examined the linkages among the activity and travel decisions of the male and female heads of the household. The matrix of causal linkages and the correlations in the error terms are instrumental in capturing the relevant inter-dependencies.

Meka *et al.* (2001) have explored the interdependencies in the non-work trip frequency, activity- and travel-durations between household adults using data from Florida. This study indicates a complementary relationship between the non-work activity engagements of the household heads, *i.e.,* increasing non-work activity and travel durations of one adult is found to increase the corresponding durations of the other adult. Thus, this study highlights the possibility that a transportation policy action that directly impacts one household adult can also result in changes in the travel patterns of the other household adult, who may not be directly impacted. While insightful, the use of a single "non-work" activity type as the unit of analysis may limit this model's capability to further discern the exact nature of interactions.

Golob and McNally (1997) further disaggregated the activity types and explored interpersonal interactions in the activity and travel durations of the male and female household heads for three categories: work, maintenance, and discretionary activities. The model system also accommodated the censored nature of duration, since several individuals may not participate at all in specific activity types. The models were estimated using a two-day activity-travel survey data from Portland. This study brings out important gender differences in the roles played by the household heads. Specifically, increasing the work duration of the male was found to increase the female's maintenance activity and travel durations. However, increasing the work duration of the female was not found to influence the male's maintenance activity duration or travel times.

The two studies presented above did not explicitly distinguish activities undertaken jointly by the household heads from activities pursued independently. In contrast, research undertaken by Fujii *et al.* (1999) examined individuals' preferences for joint versus independent activity engagement using reveled preference (RP) and stated preference (SP) data collected from the Osaka-Kobe metropolitan area in Japan. This study did not examine time-use by activity purpose;

rather, it studied time use based on companion type and activity location, as determined in the following categories: in-home alone, in-home with family, in-home with others, out-of-home alone, out-of-home with family, and out-of-home with others. Some interesting results from this study include (1) workers who work long hours tend to engage more frequently in out-of-home activities with family members, and (2) persons with children prefer to spend more time in-home jointly with family.

Focusing on only maintenance activities, a recent study by Schwanen *et al.* (2004) examined the decisions of the male and female heads of the household to undertake independent versus joint activities. This study used data from The Netherlands. Increasing frequency of grocery shopping by the female was found to negatively impact the frequency of shopping undertaken by the male and jointly by both. However, in the case of shopping for consumer goods, increasing participation of the wife was found to increase the participation of the husband. Further, this analysis also suggests that joint activity participation is perhaps not a strategy employed by households to overcome constraints due to non-availability of multiple vehicles. Rather, joint maintenance activity participation is found to be impacted by accessibility to opportunities, *i.e.,* greater the number of stores near home, lesser is the likelihood of joint activity engagement by the spouses.

The study undertaken by Van Wissen (1991) using data from the Dutch Longitudinal Mobility Panel examined independent and joint *weekly* time allocation by household heads for shopping, visits, and recreational activities (almost all the other studies have used the more conventional single-day or two-day activity-travel survey data for analyses). The male's work duration was found to negatively influence his shopping duration but positively impact his wife's shopping duration, suggesting that the male's work duration indirectly leads to substitution effects in the shopping activity participation decisions. Further, the female's non-work activity participation durations was found to positively influence the corresponding non-work activity participation durations of her husband.

The next three SEM-based studies discussed here have explored the household's auto-ownership choices simultaneously along with short-term inter-dependent activity-travel choices. These studies examine not only the impact of the number of automobiles on the inter-personal interactions in activity-travel participations but also the impact of inter-dependent activity participation needs of the different household members on automobile ownership decisions. None of these three studies, however, explicitly distinguish between independent and joint activities.

Simma and Axhausen (2001) studied the linkages among the number of maintenance and leisure trips undertaken by the male and female, their overall daily travel distances, and the number of automobiles in the household. This analysis was undertaken using data from nuclear families in Upper Austria. The activities of the two household heads were found to be mutually dependent with the male's maintenance trips positively impacting female's trips for the same purpose and the female's leisure trips positively impacting the male's leisure trips. Further, the traditional sex-specific division of household labor was found to be associated more with elderly households, suggesting a possible change in traditional activity-travel patterns over time. Finally, the number of automobiles in the household was found to be strongly dependent on the wife's employment status (employed wives are more likely to have their own car). The employed women were also found to travel longer distances in the overall but make fewer maintenance trips. The decreased number of maintenance trips of the employed wife was partially offset by increased number of maintenance trips of the husband. Hence, this study indicates that the trend of increasing women in work force has substantial implications on automobile ownership decisions of the household and the daily travel patterns of the spouses.

Golob (1997) examined the inter-dependencies among the male and female activity-travel participation, vehicle ownership of the household, and the total vehicle miles of travel on all household vehicles using a structural equations model system. The activity participation was quantified in terms of the duration invested in each of in-home work, out-of-home work, out-of-home maintenance and out-of-home discretionary activities. The results indicate that the male's travel demand is influenced by the female's out-of-home work and maintenance activity durations and in-turn the female's travel demand is influenced by the male's non-work activity durations. Automobile ownership was found to be significantly influenced by only the male's activity durations. Retail accessibility, defined as the total retail employment within 1 mile of the household, was found to positively impact the male's maintenance activity duration but negatively impact the female's maintenance activity duration. Finally, the study also finds very significant positive error correlations between the male and female activity and travel demand equations. This suggests the presence of common unobserved factors, which affect the daily activity-travel patterns of the spouses.

The study undertaken by Ettema *et al.* (2004a) is the third research effort focusing on modeling both activity-participation decisions along with household automobile ownership decisions. Data collected in the Amsterdam-Utrecht corridor in The Netherlands was used to analyze the linkages among the subsistence, in-home maintenance, and out-of-home maintenance activity choices of the spouses (along with automobile ownership decision of the household). Increased subsistence (work) duration of a person was found to decrease that person's in-home maintenance frequency and duration but increase his/her spouse's in-home maintenance frequency and duration suggesting a "compensating" effect. Higher engagement of the female in maintenance activities was also found to increase the male's maintenance engagement. Among the spatial variables, the density of the residential area was found to impact in-home task assignment. Specifically, the males in households in low-density areas were found to more time in in-home maintenance whereas the females spent lesser time. Finally, this study did not find any significant impacts of the activity participation characteristics on the automobile ownership decisions of the household.

2.3.1.2 Seemingly unrelated regressions (SUR) approaches

As already indicated before, the second major methodology within the class of continuous choice models adopted for modeling household interactions is that of seemingly unrelated regressions. The seemingly unrelated regression models allow the estimation of two or more equations with a specified error correlation. Zhang *et al.* (2002, 2004a), Zhang and Fujiwara (2004) and Zhang *et al.* (2004b) have applied the SUR approach in the context of modeling inter-dependent time-use decisions accommodating both independent and joint activity participations. As already discussed before, these models are based on an underlying household utility maximizing model that explicitly accounts for the presence of two decision makers. Data from The Netherlands and from Japan have been used in the empirical analysis. While insightful in addressing the different possible decision making mechanisms that households might employ, a methodological limitation of these studies is that they do not account for the censored nature of the activity durations arising as a consequence of several individuals not participating in specific kinds of activities during the day.

2.3.2 Discrete Choice and Shares Modeling Approaches

Several studies on interpersonal interactions have used methods that may be broadly classified under discrete-choice or share models. Scott and Kanaroglou (2002) developed trivariate ordered-probit models to jointly determine the number of non-work episodes undertaken by household heads. The interactions are captured through correlations in unobserved factors affecting the propensity of the household adults to undertake independent and joint episodes. Separate models were estimated for three kinds of households: no-worker households, single-worker households, and dual-worker households using data from Canada. In the case of no-worker households, the error correlations between the male and female independent non-work activity participation propensities was found to be positive suggesting a complementary relationship between the independent non-work activity participation of the male and the female heads. In contrast, the error correlation between the female and joint activity participation propensities was negative. Similarly, in single worker households, the error correlation between the worker's non-work activity participation and joint non-work activity participation was found to be negative. However, if only the worker is a licensed driver, the couple is found to be more likely to undertake joint non-work activities. In dual-worker households, if the couple commute together, they were also found to be more likely to undertake joint non-work activities. Further, the error correlation between the male and female independent activity participation propensities was positive. In the overall, this study highlights several interdependencies among the non-work activity participation choices of the household heads due to both observed and unobserved factors. However, the use of a single, aggregate "non-work" activity type as thee unit of analysis limits the models ability to discern differences in the nature of interactions induced by different types of activities.

In contrast to the above study, research by Ettema *et al.* (2004b) examine inter-personal interactions impacting the participation in six different activity purposes: work, out-of-home household activities, in-home household activities, out-of-home recreation, in-home recreation, and out-of-home personal business. Separate logit models were estimated for the participation of the male and female in each of the six activity purposes (hence, there are twelve models in all). Thus, this approach does not model the activity participation choices of the spouses simultaneously. Rather, in models for each of the household heads, the activity participation choices of the spouse were taken as exogenous variables to capture the inter-dependencies between the activity participation decisions of the spouses. This study indicates that if one of the spouses undertakes in-home leisure activities, the probability of the other spouse undertaking out-of-home activities decreases possibly suggesting a desire to undertake joint in-home activities. Also, the probability of any person undertaking out-of-home recreation activities increases if the partner also undertakes these activities.

The proportional shares model developed by Gliebe and Koppelman (2002) determines the proportion of time invested, independently and jointly, by each of the two household heads, in different types of activities (subsistence, maintenance, leisure, and home for independent participation and maintenance and leisure for joint participation). Thus, this modeling approach captures both the intra-personal and inter-personal trade-offs in activity participation decisions (the theoretical underpinnings of this work has already been described). The empirical model results indicate employed members have a proportionately greater impact on joint activity decision making, presumably due to their greater time constraints. Further, adults in households with children were found to be less likely to undertake joint maintenance and leisure activities. Availability of an automobile for personal use for each of the adults was found to increase independent non-work time investments of the household heads.

Wen and Koppelman (1999, 2000) focused on modeling the household interactions impacting choices related to household maintenance activities, explicitly recognizing that maintenance activities are undertaken to serve household needs as opposed to individual needs. This study comprises two nested-logit model systems. The first model system models household maintenance stop generation, allocation of these stops to one of the household heads, and the allocation of the household automobiles for undertaking the generated maintenance stops. The second model system, conditional on choices related to number of maintenance stops and the allocation of these stops and autos, determines the tour generation for each household adult and the assignment of maintenance stops to these tours. Joint activity participation is not considered by this modeling system. The empirical results indicate that in single vehicle households, the vehicle is very likely to be assigned to the person undertaking maintenance stops. Further, the study also finds strong linkages among the various generation, allocation, and organization choices considered in the analysis.

All the efforts described above (both discrete and continuous choice models) have focused on two-adult households and have limited their analysis to the interaction between the two household heads. In contrast, the regional-level tour-based travel demand model system developed for the Mid-Ohio Regional Planning Commission (MORPC) accommodate interactions among the household members in many different kinds of single- and multi-adult households (Vovsha *et al.*, 2003, 2004b, 2004c, and 2004d), in addition to capturing intra-person trade-offs made by persons in making their daily activity-travel choices. This work address several practical considerations involved with large-scale comprehensive regional modeling system.

2.3.3 Exploratory Analyses

The studies reviewed in this section have not developed models of inter-dependent activity-travel choices of household members. Rather, these studies have focused on conducting exploratory analyses of the various linkages among the activity-travel patterns of household members. Several useful insights can be gained from such descriptive analyses, which, in turn, can inform the empirical model specifications.

Chandrasekharan and Goulias (1999) analyzed the Puget Sound Transportation Panel Data to compare the characteristics of solo and joint trips and also solo and joint trip-makers. In a substantial fraction of the joint trips (about 65% of all joint trips in the sample), the trip makers are either spouses or a parent with children. Further, 7% of the joint trips involved both parents and children. This clearly indicates that joint travel is most likely to be undertaken with family members. About 17% of the joint trips in the sample represented formal car-pooling arrangements. For further analysis, the study did not distinguish between these different types of joint trips. In the overall, younger persons were found to make more joint trips and individuals from households with only one vehicle were also found to make more joint trips. Similarly, individuals in households with children were found to be more likely to undertake joint trips, presumably these are trips made by the parent with children. Return-home, shopping, and personal business were the trip purposes that were found to be most likely to be joint trips. This is interesting, as one would expect trips undertaken for leisure purposes to be very likely to be undertaken jointly. This study does not appear to have explored such trip-purposes in their analysis.

In contrast to the above study, which focused on individual trips, research by Kostyniuk and Kitamura (1983) compare the characteristics of joint and independent *paths* of household members. The path was defined as the complete space-time trajectory of the household members during the evening period. Data from the Detroit area was used in the analysis and several interesting and intuitive results are observed. Couples without children and couples who are both workers are found to have joint paths with contact points other than home, suggesting that these couples meet at some out-of-home location and pursue activity-travel from that point jointly. Presence of children in the household and the availability of multiple automobiles favor independent paths for the husband and wife. Finally, the total out-of-home time was found to be longer when the evening activity-travel patterns of couples involved joint paths.

Kitamura (1983) has examined the serve-passenger activity participation behavior using data from the Detroit area. This study finds evidence for the hypothesis that serve-passenger activities are undertaken within strict space-time constraints and consequently are not chained with other activity purposes. If at all chained, serve-passenger activities were found to be chained with flexible non-obligatory activity purposes. Quite intuitively, both workers and nonworkers are found to be more likely to undertake serve-passenger activities when school-age children are present in the household. In the overall, this study highlights that the strict space-time fixities and interpersonal coupling constraints in undertaking serve-passenger activities impacts the overall travel behavior of individuals (especially non-workers).

The next two studies (Vadarevu and Stopher, 1996 and Stopher and Metcalf, 1999) reviewed here compare the relative time-use patterns of the household adults across five different life cycle stages: (1) single, employed person, (2) multi-adult households, at least one worker and no children, (3) single- or multi-adult households, at least one worker and young (non-school going) children, (4) single or multi-adult households, at least one worker and at least one school going child, (5) single- or multi-adult households, no workers and no children. The researchers hypothesize that the household time allocated to mandatory, flexible, and optional activities is impacted by the life-cycle stage of the household. Data from Boston and Salt Lake City are analyzed to provide support to their hypothesis. The relative amounts of time allocated to these activity types by the different adults in the households is also found to be dependent on the gender and the employment status of the person. Further, the impact of gender and employment status was also found to vary by the household life-cycle stage.

2.4 Methodological Advances

The intent of this section is to present a review of the progress in specification and estimation of choice models. In the context of this research work, advances in three specific methodological areas are of interest: (1) mixed-logit models, (2) hazard-based duration models, and (3) discrete-continuous models. Each of these is discussed in detail below.

2.4.1 Mixed-Logit Models

The Multinomial Logit (MNL) model has long been a very popular approach for discrete choice modeling (See for example, Ben-Akiva and Lerman, 1985 for structure, properties, and estimation procedures of the MNL model). The strength of this approach stems from the fact that this approach is consistent with the economic theory of random-utility maximization. Further, the model assumes an elegant closed-form mathematical structure as a consequence of assumptions of (1) independently and identically gumbel-distributed (IID) error terms across the choice alternatives and across the decision makers, and (2) response homogeneity. However, it has been found that it is necessary to relax these strong assumptions in many choice contexts (Bhat, 2000a).

The mixed-logit models (also called as logit-kernel models) represent a class of flexible discrete choice models that relax the underlying assumptions of the MNL models in three main ways: (1) allow correlations in the error terms across the choice alternatives, (2) allow the variances of the error terms to be different across the choice alternatives, and (3) capture response heterogeneity by the specification of random coefficients on the explanatory variables. Ben-Akiva *et al.* (2001) present details on the specification, identification, and estimation of the mixed-logit models. Bhat (2000a, 2003a), and Hensher and Greene (2003) provide detailed reviews on the state of the art in the mixed-logit model specification.

The mixed-logit models, while relaxing the restrictive assumptions of the MNL model lead to probability expressions that do not have closed-form mathematical structures. The computation of the probabilities involves multi-dimensional integration of the MNL formula over the distribution of the random parameters (see for example, Bhat, 2003a). The evaluation of such probability expressions involving multidimensional integration requires simulation techniques. In this context, Bhat (2001a) proposed the use of a Quasi-Monte Carlo (QMC) simulation method using the Halton sequence (see Train, 2000) for the simulation-evaluation of such multidimensional integrals. This QMC based methodology has been found to be superior to more conventional Pseudo-Monte Carlo (PMC) methods in terms of both the accuracy of the model parameters as well as the computational time (see, for example, Bhat, 2001a; Train, 2000; and Hensher, 2001). Subsequent research has focused on the use of scrambled and randomized QMC sequences (Bhat, 2003a) for estimation in order to facilitate the determination of the simulation error.

In the overall, the importance of the mixed-logit models lies in its flexible, yet computationally efficient, structure and its ability to address both response heterogeneity and relax IID error assumptions within a single framework (Bhat, 2003a). Further, advances in QMC-based simulation techniques have provided the analysts with powerful tools for the estimation such flexible discrete choice model structures. Thus, mixed-logit models are considered to represent the most promising state of the art in discrete choice modeling (Hensher and Greene, 2003).

2.4.2 Hazard-Based Duration Models

The Hazard-based duration models are suited for modeling duration or time related phenomenon. Specifically, this class of models focus on the probability of the termination of a duration spell given that the spell has already lasted for a certain amount of time (Kiefer, 1988; Hensher and Mannering, 1994). Thus, this methodology captures the duration-dependence dynamics, *i.e.,* the impact of the duration already invested in an activity on the termination of participation in the activity. The probability of termination is specified in terms of a hazard function. The three main structural component of this hazard function are (1) the distribution of the baseline hazard, (2) the function capturing the covariate effects, and (3) control for unobserved heterogeneity. Bhat (2000b) describes alternate specifications of the three structural components of the hazard function and the model estimation procedures.

The above discussion was focused on the modeling of a single duration spell with the termination of the spell triggered by a single event (for example, the end of a trip with the start of an activity). The hazard-based approach has also been extended for application in the following contexts:

(1) Simultaneous modeling of multiple duration spells

This methodology is focused on the simultaneous determination of multiple duration decisions and involves the joint estimation of multiple hazard-duration models with error correlations across these different models. Srinivasan and Guo (2003) present a simultaneous hazard-duration model system for the joint determination of activity duration and travel time. Bhat *et al.* (2004b) present a more general multiple hazard-duration model system and apply it in the context of the simultaneous determination of the interactivity duration for five different activity purposes.

(2) Modeling of multiple duration-ending outcomes (or exit states)

This methodology recognizes that the termination of a duration spell can result in one of several outcomes or exit-states and seeks to capture the effect of the exit state on the duration dynamics. For example, the end of a trip can result in one of several different activity types such as shopping, work, home, etc. and this outcome at the end of the trip can influence the trip duration. Han and Hausman (1984) have developed a "competing risks model" to capture such multiple-exit states. Bhat (1996a) has proposed a generalization of this approach that explicitly models the exit states along with the duration models corresponding to each potential exit state.

In the overall, hazard-based duration models offer a valuable tool to model temporal dynamics in several transportation-related phenomena. It is being increasingly applied to transport modeling, especially in the context of activity-based travel analyses (see Hensher and Mannering, 1994; Bhat, 2000b; Bhat *et al.*, 2004b).

2.4.3 Discrete-Continuous Models

The mixed-logit models discussed in Section 2.4.1 focus on modeling discrete choices whereas the hazard-duration models discussed in Section 2.4.2 and the more conventional linear regression models are useful for modeling continuous choices. In addition, there are several instances in transport modeling, which involve inter-dependent discrete and continuous choices. For example, the type of activity to undertake and the activity duration, the type of automobiles to own and the usage of each vehicle, the choice of buying discounted transit coupons and transit trip frequency, etc. There are two major approaches to modeling such inter-dependent discrete and continuous choices. In the first approach, which is consistent with the economic theory of random-utility maximization, one specifies the indirect utility function for the discrete choice and derives the equation for continuous choice (*i.e.,* the "demand" equation) via Roy's Identity (see for example, Mannering and Hensher, 1987 or Train, 1993). Thus, this method introduces strong theoretical linkages between the discrete and continuous choices. However, it may not always be straightforward to derive the required continuous demand equation from the utility functions of the discrete choice alternatives (see for example, Kockelman, 1998). The alternative approach is the specification of a model system that is based on "reduced-form" utility representations (Mannering and Hensher, 1987). In such an approach, the theoretical/behavioral linkages between the discrete and continuous components can become rather arbitrary. However, this methodology also leads to the possibility of specifying estimatable models with very flexible linkages between the discrete and continuous components, as is often needed to fit the data well. Some recent applications of such flexible discrete-continuous models include an analysis of the commute activity-travel behavior examining the choice of activity type, activity duration, and travel time by Bhat (2001b) and an analysis of the post-home-arrival activity-travel behavior examining the choice of activity type, home-stay duration, and activity duration by Bhat (1998).

A recent and very significant development in the area of modeling discrete-continuous choices is the utility-theory based Multiple Discrete-Continuous Extreme Value (MDCEV; Bhat, 2004) model. This model structure is developed in the context in which a decision maker can choose *one or more* alternatives from the available choice set (the conventional choice models assume that only one alternative is chosen from the choice set). Further, the MDCEV model also explicitly accommodates satiation effects (*i.e.,* diminishing marginal returns with increase in the consumption of the continuous choice alternatives). The MDCEV model has an elegant closed-form expression for the discrete-continuous choice probabilities and collapses to the MNL structure in the case of single discreteness. Finally, Bhat (2004) also presents the mixed-MDCEV model incorporating heteroscedasticity and/or correlations in unobserved characteristics affecting the demand of the different alternatives. This extension of the MDCEV model to the mixed MDCEV model is analogous to the extension of the MNL model to the MMNL structure.

2.5 Summary and Contributions of Current Research

There has been, quite clearly, a phenomenal interest in the development of activity-based travel-demand models. Most of these models have, at best, accommodated household interdependencies by using household characteristics as explanatory variables in models describing choices of individuals. More recently, there has been increasing interest to explicitly capture the impact of household interactions in activity-travel decision-making. These studies, reviewed in detail in this chapter, indicate several ways in which the activity-travel patterns of household members are inter-linked. The intent of this dissertation is to contribute to this growing area of research by modeling the inter-personal interactions and household needs and constraints in the shaping of daily activity participation decisions. We present a framework for modeling the interdependent decisions of the spouses in nuclear family households regarding participation in different types of activities, both in-home and out-of-home. The proposed approach also captures intra-personal trade-offs in choices about participating in different types of activities. This research is intended as an important component in the overall development of an operational, activity-based, travel-demand forecasting systems that comprehensively model various intra-personal and inter-personal linkages in daily activity-travel choices. Methodologically, this research builds upon the state of the art in choice modeling to specify flexible discrete-continuous econometric models.

Chapter 3 The Modeling Framework

3.1 Introduction

This chapter of the dissertation first presents a conceptual framework for modeling the overall daily activity and travel generation process in a household (Section 3.2). Within this overall conceptualization, the focus of this research is on incorporating appropriate inter-personal interactions in the modeling of the daily activity participation (or generation) choices of household adults. Towards this end, Section 3.3 identifies the activity typology employed in this work and the interaction effects associated with the different activity types. Section 3.4 then presents the detailed framework for modeling the generation of the different types of activities. This section also identifies the overall sequence of models as well as the econometric structure of the individual model components. The detailed mathematical formulations of the econometric structures are described in the next chapter.

3.2 The Daily Activity-Travel Pattern Generation Process

The daily "activity-travel pattern" of a person may be defined as the set of all activity episodes undertaken by the individual during the course of a day, with each of the episodes being described in terms of the type of activity, its position within the sequence of all activities undertaken during the day, the location of participation, duration of participation, the time of day, and the characteristics of the travel (travel mode, route, duration, etc.) to that activity episode.

This research draws from earlier works of Bhat and Koppelman (1993) and Wen and Koppelman (1999,2000) in its overall conceptualization of the process of the generation of activity-travel patterns of individuals within a household. This conceptual structure is presented in Figure 3.1. The daily activity and travel decisions of household members are made conditional on several factors which may be broadly classified into: (1) individual and household characteristics and (2) the activity-travel environment characteristics.

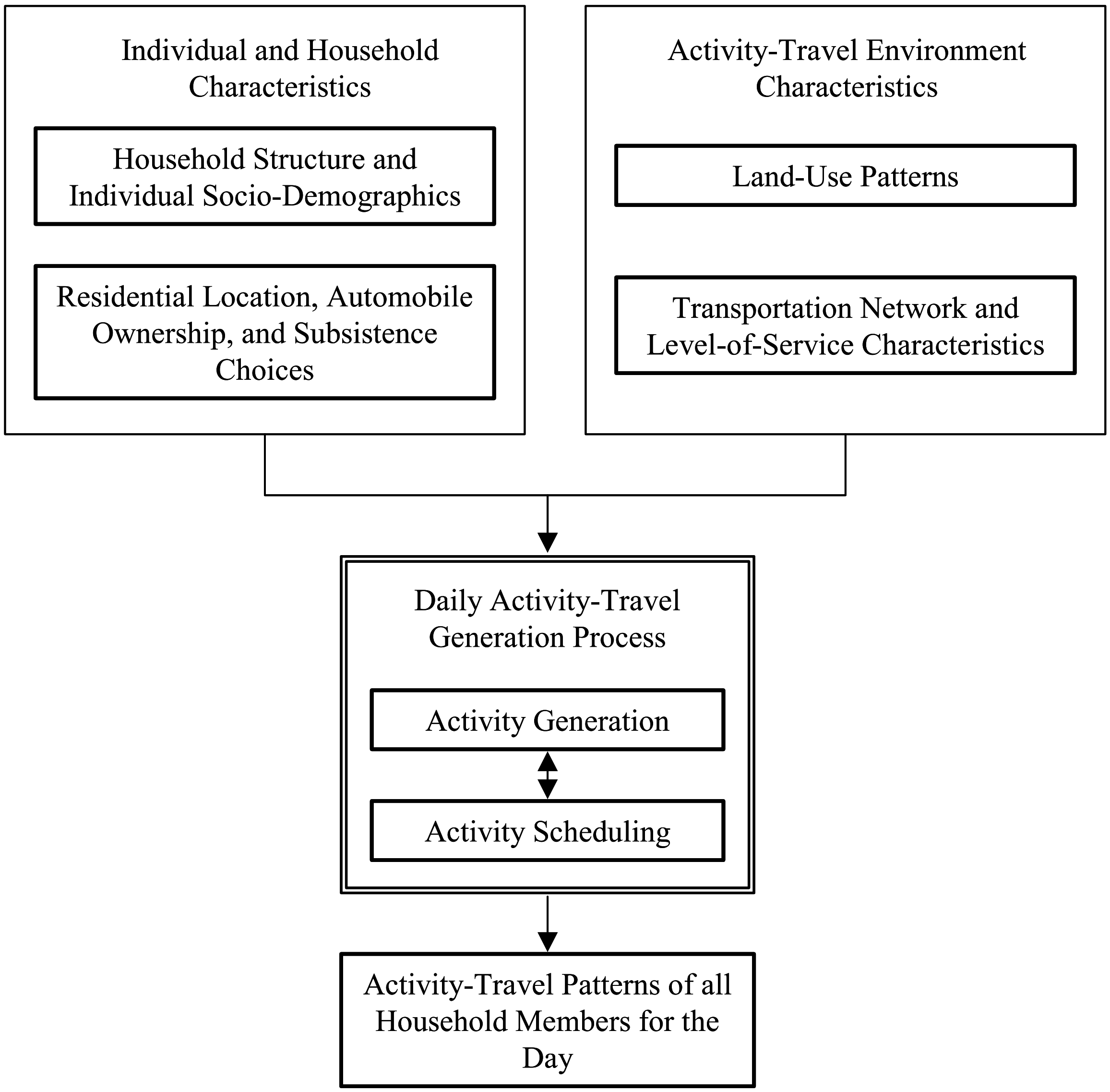

Figure 3.1 A Conceptual Framework for Daily Activity-Travel Generation

The individual and household characteristics include (1) the structure of the household (single adult, couple, nuclear, extended family, etc.) and demographic characteristics (such as age, gender, and ethnicity) of its members and (2) residential location, automobile ownership, and subsistence choices (decision of different members to work, employment type, work hours, work location, etc.). The household structure and socio-demographic characteristics of the household describe the life-style and the consumption patterns its members. Thus, these characteristics define the needs and desires of the household and the roles played by different members in the household in satisfying these needs. The long-term choices of the households (*i.e.,* residential location, automobile ownership, and subsistence choices) impose spatial, temporal, and mobility constraints that critically dictate the daily activity participation behavior of all household members. For example, the household location and availability of automobiles for use determines the spatial set of activity centers (shops, restaurants, movie theaters, etc.) that may be accessed by the household members for activity participation. The employment choices of individuals may require them to be at the place of work for certain periods of the day, thereby imposing spatial and temporal constraints on their overall activity participation.

The activity-travel environment is described by both the land-use patterns (*i.e.,* location of shopping malls, parks, residential areas, etc.) and the transportation network and level-of-service characteristics (such as highway travel times during different times of the day, availability and frequency of transit). These define the spatial distribution of opportunities offered by the urban area for activity participation and also the accessibility to these activity centers. Further, unlike individual and household characteristics, the activity-travel environment can be directly controlled by institutions responsible for transportation and land-use planning. The control measures adopted by these urban planning agencies may be "supply" strategies (such as transportation infrastructure enhancements) to provide for the growing needs of the population or "demand management" policy actions (such as congestion pricing) so as to influence the activity-travel decisions of people towards efficient use of available infrastructure. Hence, a knowledge of the impact of the activity-travel environment on the activity-travel patterns is of utmost importance to planning agencies.

The individual and household characteristics and the activity-travel environment together define the needs, desires, opportunities, and constraints within which household members make daily activity and travel related choices. This daily decision-making process within a household is represented as being composed of two inter-related components: activity generation and activity scheduling. The activity generation process primarily describes the decision of the household members to undertake different activities during the day. This decision to undertake activities may also simultaneously determine one or more attributes of the activities such as the location of activity participation, time-of-day, and duration. The scheduling process determines the sequencing of all generated activity episodes, the location and time of day of participation of each episode, and the means of travel between successive activity episode locations. The scheduling decisions are made within the constraints imposed by the activity-generation decisions. At the same time, scheduling considerations also impact choices about the different activities to be undertaken during the day. Thus, the activity generation and scheduling components of daily decision-making are interlinked and the outcomes of the two components together define the complete activity-travel patterns of all household members.

Within this overall conceptualization, the focus of this dissertation is on modeling daily activity generation of the adults in a household as an outcome of inter-personal interactions among the adults. The impact of detailed activity scheduling choices on activity generation decision-making is not considered. However, measures of accessibility to activity centers from home and work, transportation level-of-service characteristics, and spatio-temporal fixities imposed by activities such as work are used as proxies in activity generation models to capture the effect of scheduling constraints on activity-generation decisions.

3.3 Activity Typology and Household Interaction Effects

Individuals undertake several types of activities (such as, work, shopping, recreation, and social visits) during the day at both in-home and out-of-home locations. The nature of the household interactions impacting activity-generation decisions can be expected to be different for different types of activities. Hence, as a first step towards developing a framework for modeling household interactions in daily activity generation, this section presents the activity typology used in this study and describes the nature of interactions among the household adults associated with each type of activity.

The activities that an individual undertakes during the course of the day are broadly divided into the following three types: mandatory, maintenance, and discretionary activities (very similar three-way classifications have also been adopted by Bhat and Koppleman, 1993 and Vadarevu and Stopher, 1996). Activities such as work that are undertaken with significant “regularity” primarily constitute the set of *mandatory* activities. In addition, in households with school-going children, trips to drop-off children at school and pick them up later on may also be mandatory for the household adults. The characterizing feature of mandatory activities is that one or more attributes such as frequency, location, and time-of-day are fixed over long periods of time (Vadarevu and Stopher, 1996). Therefore, the daily mandatory activity participation characteristics of household members are primarily based on longer-term individual- and collective-decisions with relatively minimal impact of short-term interactions. However, the mandatory activities undertaken by each household member may critically impact the non-mandatory activity participation decisions of *all* household members. For example, a person who works long hours may not have adequate time for performing household chores requiring a non-employed person in the house to pick up that responsibility.

Maintenance activities are those that are motivated by household needs and are undertaken for the upkeep of the household. These activities may be undertaken either in-home (for example, household chores, cooking, and cleaning) or out-of-home (for example, grocery shopping, and paying bills). Although maintenance activities are also essential for the functioning of the household, unlike in the case of mandatory activities, households may have relatively more flexibility in choosing the frequency, duration, time of day, and location of activity participation. Undertaking of maintenance activities results in the production or procurement of goods (such as clean homes, and food) that is available for consumption for all household members. Hence, the choices about maintenance activity participation are often an outcome of household decision-making involving all or many of the household members rather than the personal decision of any one household individual. In this collective decision making process, the household may choose to allocate the various tasks to one or more members to achieve efficiency in pursuing household responsibilities. Therefore, maintenance activity participation characteristics are a consequence of household interactions, even if the resulting activity itself is undertaken independently by one of the household members.

Discretionary activities are those that are undertaken for social, recreational, or other personal reasons, either in-home or out-of-home. Among the three types of activities; mandatory, maintenance, and discretionary; the discretionary activities offer the maximum flexibility in terms of several spatial and temporal dimensions of activity participation. Unlike maintenance activities, discretionary activities are generally associated with the consumption of the individuals undertaking the activity. Hence there are no responsibilities to share in the undertaking of discretionary activities. However, household members could choose to undertake discretionary activities jointly (such as going to the movies together), thereby involving multiple household members rather than a single individual in the decision-making. Thus, joint activity participation quite naturally introduces linkages in the activity-travel patterns of the household members. Further, household members generally consider the impact of their choice of personal actions on other household members and the constraints and needs of other members while making daily activity-travel decisions (Jones *et al.*, 1983). Such considerations are likely to be the strongest in the case of the planning and execution of flexible, discretionary activities. Thus, the discretionary activity participation decisions of all household members can be expected to be inter-dependent, even in the absence of joint activities.

3.4 A Framework for Modeling Weekday Activity Generation in Active Nuclear-Family Households

The previous section presented the activity classification scheme to be used in this study and identified the different types of interaction effects associated with each of the three activity types. The daily activity generation of household members can be modeled in terms of time invested by each household member in each of maintenance, mandatory, and discretionary activities and capturing the appropriate interaction effects characterizing each activity type. However, the sequencing of the decisions relating to mandatory, maintenance, and discretionary activities depends on several factors. For, example, weekday activity travel behavior may be dictated by the fixities imposed by the mandatory activities, while weekend activity participation may be driven by discretionary activity participation desires. Similarly, active households (households with one or more working adults) may face significant time pressure requiring prioritizing of the different kinds of activities. On the other hand, retired households (households with all adults retired or not-employed) may not face the consequences of constraints imposed by mandatory activity participation.

In this research, we focus our analysis in the context of weekday activity generation in active, nuclear family, households (such households include at least one employed adult, and comprise a male-female couple; further, any child present in the household is less than 15 years of age). In addition, the focus is on the modeling of the activity participation choices of the two household heads; the activity and travel choices of the children in the household are not modeled in this research.

Within the above research context, we specify a sequential framework (Figure 3.2) for modeling daily activity generation. This sequencing is based on the hypothesis that households operating within the time constraints imposed by mandatory activities prioritize their activity participation choices based on the relative importance of the different activities and the constraints within which the different activities are to be undertaken (Golob, 1997; Goulias, 2002; Ettema *et al.*, 2004a). In this framework, decisions about mandatory activity participation are assumed to be made first by the household adults since these decisions are dictated predominantly by long-term subsistence choices and subsequently impose substantial constraints on the overall non-mandatory activity participation during the day. The decisions about maintenance activity participation are made subsequent to mandatory activity choices, recognizing the importance of these activities in the overall upkeep of the household. Within the class of maintenance activities, decisions about in-home maintenance activities are made first, followed by the decisions about out-of-home maintenance activities. This sequencing is motivated by the observation that in-home maintenance tasks are undertaken on a daily basis unlike out-of-home maintenance tasks and hence might enjoy a higher priority within the household's activity-participation decision sequence. Choices about discretionary activities, which are the most flexible among the three types of activities, are made finally, conditional on choices related to mandatory and maintenance activities. Decisions about in-home and out-of-home discretionary activity participations are made simultaneously. Similarly, decisions regarding solo and joint activity participations are also assumed to made simultaneously.

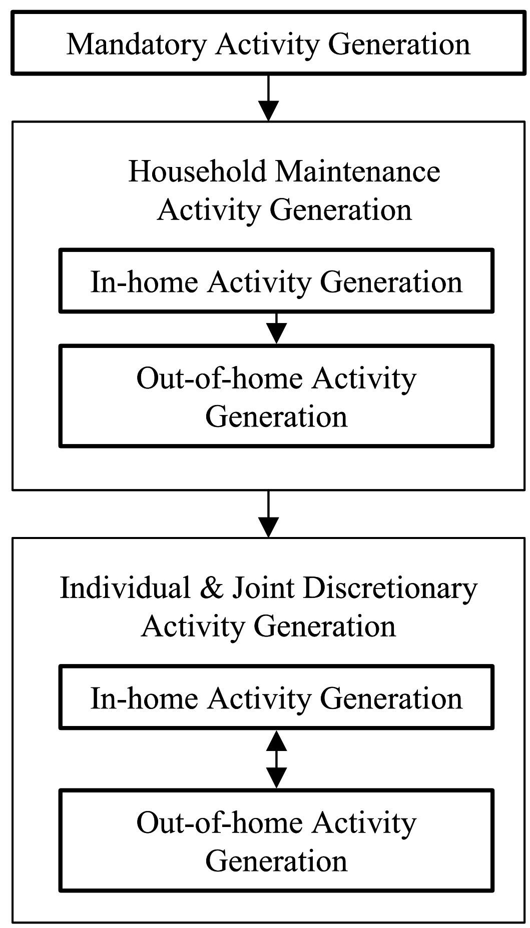

Figure 3.2 Framework for Modeling Daily Activity Generation

The mandatory activity participation decisions of the household adults are not explicitly modeled in this research considering the relatively minimal short-term interactions between the household adults relating to these decisions. These decisions are assumed to be exogenous to our empirical modeling system, which comprises three model components: (1) the in-home maintenance activity generation model, (2) the out-of-home maintenance activity generation model, and (3) the discretionary activity generation model.

The in-home maintenance activity generation is modeled in terms of the time invested by the male and female heads in household chores (Figure 3.3). Since, almost all individuals invest some time in-home in household maintenance chores, the choice variable is essentially continuous. Therefore, the time invested by each of the household heads is modeled jointly using the *seemingly unrelated regressions* modeling system.

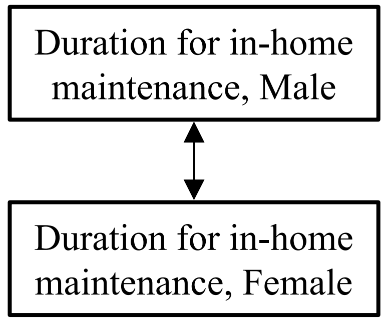

Figure 3.3 Modeling Framework for In-Home Maintenance Activity Generation

Out-of-home maintenance activity generation is modeled in terms of the decision of the household to undertake household maintenance activities, the allocation of this responsibility to one or both of the household heads, and the duration of activity participation for the person(s) allocated the responsibility (Figure 3.4). Thus, the modeling of out-of-home maintenance activity generation involves both discrete and continuous choices. The household's decision to undertake maintenance activity and its allocation comprises the discrete component of the model system, which is modeled using a mixed-logit structure to capture flexible substitution patterns among the discrete choice alternatives. Activity duration comprises the continuous component of the model system, which is modeled using the hazard-duration model structure to explicitly accommodate duration dynamics. Thus, a *joint mixed-logit hazard-duration* model structure is adopted for the modeling of out-of-home maintenance activity generation.

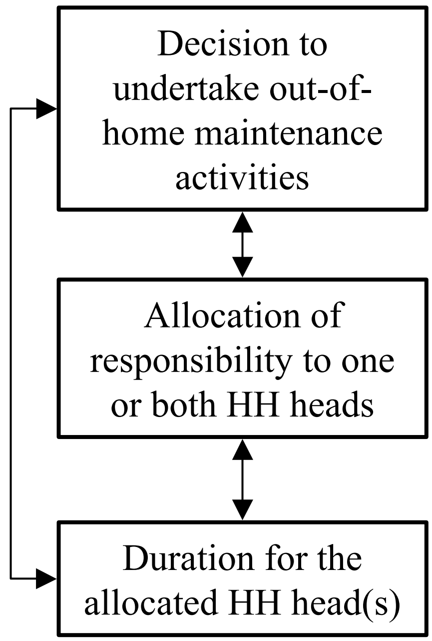

Figure 3.4 Modeling Framework for Out-of-Home Maintenance Activity Generation

The framework for modeling discretionary activity generation is presented in Figure 3.5. The household heads undertake discretionary activities either in-home or out-of-home. Further, out-of-home discretionary activities may be undertaken either independently or jointly by the household adults. Hence, the modeling of out-of-home discretionary activity generation comprises five main components: (1) male's solo in-home discretionary activity generation, (2) female's solo in-home discretionary activity generation, (3) male's solo out-of-home discretionary activity generation, (4) female's solo out-of-home discretionary activity generation, and (5) joint out-of-home discretionary activity generation of the household heads. Each of these five components involves a discrete choice variable (decision to undertake activity) and a continuous choice variable (duration of activity participation) and can be represented using a joint binary-logit/ linear-regression model system. A consideration of the impact of personal choices on the spouse's activity participation needs and, in turn, the impact of spouse's activity participation choices on personal choices lead to linkages between the discretionary activity participation choices of the male and the female heads. Further, household heads make trade-offs between in-home and out-of-home solo activity participation and also between solo and joint activity participation. Therefore, the five discrete-continuous choices are inter-linked. These linkages can be represented in terms of error correlations across the five discrete-continuous models leading to a *multiple binary-logit/ linear-regression discrete-continuous* structure for the modeling of discretionary activity generation.

The model structure discussed above represents an extension of the flexible, "reduced form"-based approach for modeling a single discrete-continuous choice (see Section 2.4.3) to simultaneously modeling several discrete-continuous choices. An alternative approach for modeling such multiple discrete-continuous choices is using the MDCEV model structure proposed by Bhat (2004). The MDCEV model, unlike the proposed approach (*i.e.*, the multiple binary-logit/ linear-regression discrete-continuous model), is theoretically grounded on the principle of utility maximization and can be expected to be considerably parsimonious in the number of parameters to be estimated. The value of the proposed approach, however, lies in its ability to accommodate more flexible linkages between the discrete and continuous choice components compared to the MDCEV approach and also capture differential effects of the same explanatory variables on the discrete and continuous components of the choice.

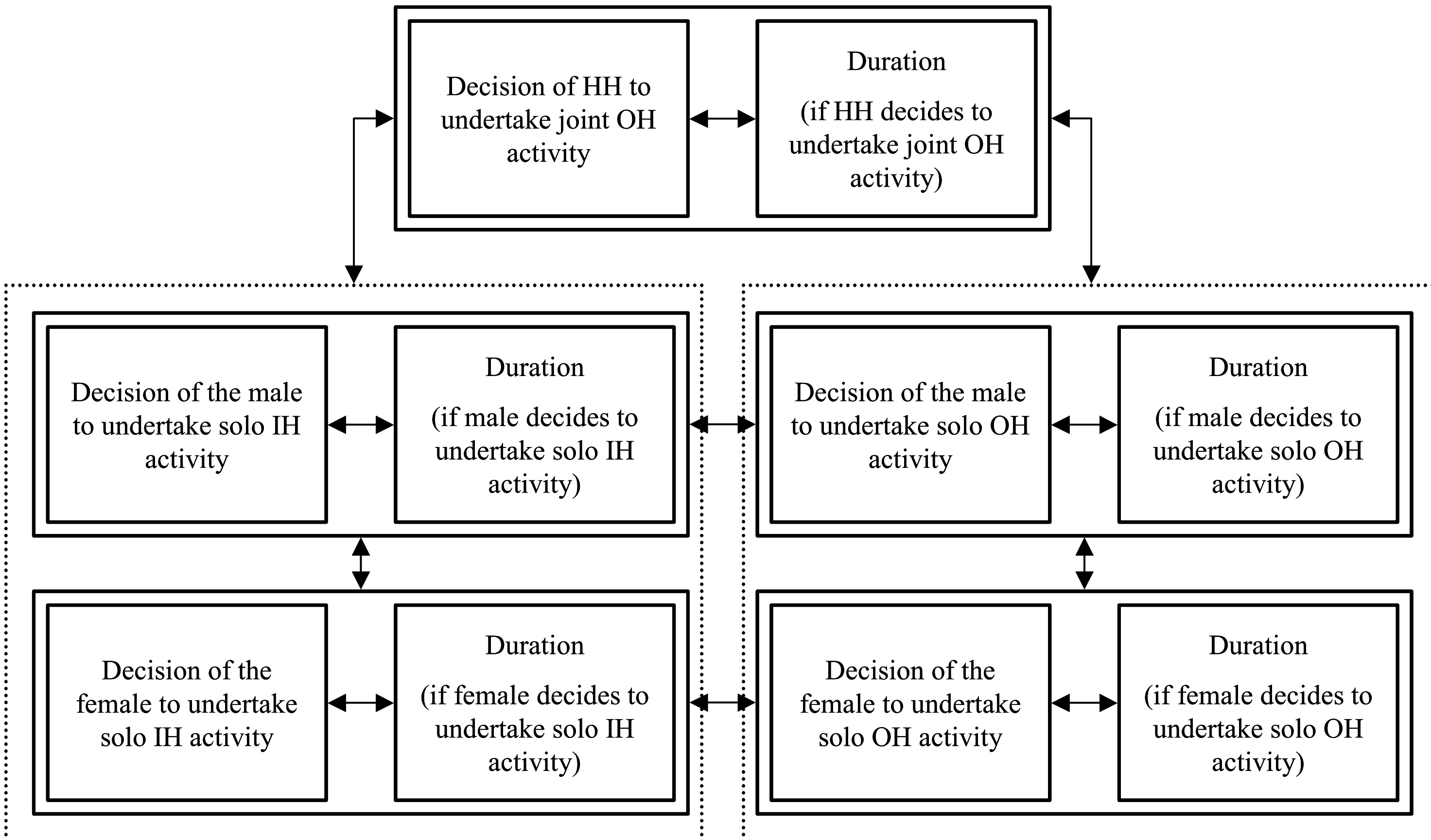

Figure 3.5 Modeling Framework for Discretionary Activity Generation

Chapter 4 Mathematical Model Structures

4.1 Introduction

This previous chapter of this dissertation developed a framework for modeling household activity generation accommodating various interaction effects. Three model components were presented and their corresponding econometric model types were identified. This chapter presents detailed mathematical structures for each of these three model components and also describes the estimation procedures. First, Section 4.2 presents the seemingly unrelated regressions model system for modeling in-home maintenance activity generation. Next, the econometric structure of the mixed logit-hazard duration discrete-continuous model system for modeling the generation of out-of-home maintenance activities is presented in Section 4.3. Finally, Section 4.4 describes the structure of the multiple discrete-continuous model for modeling discretionary activity generation.

4.2 Seemingly Unrelated Regressions Model

The in-home maintenance time investments of the male and female heads of the household are modeled simultaneously using a system of seemingly unrelated regression equations. The natural logarithm of the in-home maintenance durations of the male and female are used as the choice variables.

Let q represent the index for households (q=1,2,3,..Q). The in-home maintenance duration invested by the male and the female heads in any household may be written as:

$$\begin{aligned} t_{Mq} &= \beta_M X_{Mq} + \varepsilon_{Mq} \\ t_{Fq} &= \beta_F X_{Fq} + \varepsilon_{Fq} \end{aligned} \tag{1}$$

where, t_{Mq} and t_{Fq} represent the logarithm of the duration spent by the male and the female heads respectively in in-home maintenance, X_{Mq} and X_{Fq} are vectors of exogenous variables including a constant, and β_M and β_F are the coefficients on these exogenous variables. ε_{Mq} and ε_{Fq} represent stochastic error terms, each of which assumed to be distributed independently and identically across households. Further, the joint distribution of these two error terms takes the bivariate-normal form: $\Phi_2(0,0,\sigma_M^2,\sigma_F^2,\rho)$, where σ_M^2 and σ_F^2 are the variances of the error terms ε_{Mq} and ε_{Fq} respectively, and ρ represents the correlation between these error terms.

Within the set-up as discussed above, the probability that, in a household q, the male head invests a duration t_{Mq} and the female head invests a duration t_{Fq} is given by the bivariate normal distribution function:

$$P_q(t_{Mq},t_{Fq}) = \frac{1}{2\pi\sigma_M\sigma_F\sqrt{1-\rho^2}}\exp\left(\frac{-\left[g_q^2 - 2\rho g_q l_q + l_q^2\right]}{2(1-\rho^2)}\right)$$

where, **(2)**

$$g_q = \frac{t_{Mq} - \beta_M X_{Mq}}{\sigma_M} \quad \text{and} \quad l_q = \frac{t_{Fq} - \beta_F X_{Fq}}{\sigma_F}$$

Therefore, the log-likelihood function can be written as:

$$LogL = \sum_{q=1}^{Q} P_q(t_{Mq},t_{Fq}) = \sum_{q=1}^{Q}\left\{\left(\frac{-\left[g_q^2 - 2\rho g_q l_q + l_q^2\right]}{2(1-\rho^2)}\right) - \ln\left(2\pi\sigma_M\sigma_F\sqrt{1-\rho^2}\right)\right\} \quad \textbf{(3)}$$

The model parameters (i.e. the coefficients on the exogenous variables, β_M and β_F, the variance terms, σ_M^2 and σ_F^2, and the correlation between the error terms, ρ) are estimated using the maximum likelihood procedure.

4.3 Joint Mixed Logit - Hazard Duration Model

The discrete-continuous choice structure for out-of-home maintenance activity generation is presented in Figure 4.1. We consider grocery shopping (referred to simply as shopping henceforth) as the only out-of-home maintenance activity type in this analysis. Let i represent the index for the discrete choice alternatives, which can be one of the following: (1) Household does not shop (i=N), (2) Male is the only one allocated the shopping responsibility (i=M), (3) Female is the only one allocated the shopping responsibility (i=F), and (4) Both the male and female shop jointly (i=J). The reader will note that this choice structure assumes that the shopping responsibility is either assigned to one of the household heads or to both to be undertaken jointly, and that households do not choose a combination of these choices (for example, both household heads undertaking independent shopping, the female undertaking independent shopping in addition to joint shopping with the male, etc.) This assumption is also supported by the data used in the analysis (See Chapter 5).

The discrete component in the choice structure (*i.e.,* the household's decisions to shop and the allocation of this task) is modeled using a mixed-logit structure. The utility functions for the discrete choice alternatives are specified as:

$$U_{iq} = \beta_i Z_{iq} + \omega_{iq} + \varepsilon_{iq}, \tag{4}$$

where, U_{iq} is the indirect utility that household q derives from alternative i. Z_{iq} is the vector of exogenous variables for household q and alternative i, and β_i is the vector of coefficients on exogenous variables for alternative i. ω_{iq} and ε_{iq} are stochastic error terms. Assume that ω_q = [ω_{Nq}, ω_{Mq}, ω_{Fq}, ω_{Jq}] is multivariate normal distributed with a mean vector of zero and covariance matrix Σ. It is also independently and identically distributed across households. Assume that ε_{iq} is independently and identically gumbel-distributed across the choice alternatives and across households (this assumption leads to the multinomial logit structure for the discrete choice conditional on ω_q).

Next, define the following variable:

$$\upsilon_{iq} = \left\{ \max_{j=N,M,F,and\ J\&j\neq i} (\beta_j Z_{jq} + \omega_{jq} + \varepsilon_{jq}) \right\} - \varepsilon_{iq} \tag{5}$$

Based on the gumbel-distribution assumption on ε_{iq}, this newly defined random variable, υ_{iq}, has a logistic distribution (conditional on ω_q). Let $F_i(\upsilon_{iq} \mid \omega_q)$ represent this cumulative density function. Defining a dichotomous variable R_{iq} such that R_{iq} = 1 if household q chooses alternative i and 0 otherwise, the conditional probability (conditional on ω_q) that household q chooses discrete alternative i is given by:

$$\text{Prob}(R_{iq}=1\,|\,\omega_q)=F_i(\beta_i Z_{iq}+\omega_{iq}\,|\,\omega_q)=\frac{\exp(\beta_i Z_{iq}+\omega_{iq})}{\sum\limits_{j=N,M,F,J}\exp(\beta_j Z_{jq}+\omega_{jq})} \quad \textbf{(6)}$$

The choice of shopping duration is modeled using a hazard-based duration model system. Note that there is *no* choice of duration when the household chooses not to shop (i = N). Under each of the other three discrete choice alternatives (i = M, F, and J), there is a corresponding choice of duration (Figure 4.1). Each of these three hazard functions is specified using the proportional hazard form (Kiefer, 1998) as follows:

$$\begin{aligned}\lambda_{iq}(T) &= \lim_{\delta->0^+}\left(\frac{\Pr ob\left[T+\delta > s_{iq} \geq T \,|\, s_{iq} \geq T\right]}{\delta}\right)\\ &= \lambda_{0i}(T)\exp(-\gamma_i X_{iq}),\end{aligned} \quad \textbf{(7)}$$

where, for household q, and for each of i = M, F, and J, $\lambda_{iq}(T)$ is the continuous time hazard, $\lambda_{0i}(T)$ is the baseline hazard at time T, X_{iq} is a vector of exogenous variables, and γ_i is the vector of coefficients on these exogenous variables. The above specified hazard function can be written in the following equivalent form (Bhat, 1996b):

$$\begin{aligned}s^*_{iq} &= \ln \Lambda_{0i}(s_{iq}) = \ln \int_0^{s_{iq}} \lambda_{0i}(T)dT\\ &= \gamma_i X_{iq} + \eta_{iq},\end{aligned} \quad \textbf{(8)}$$

where s^*_{iq} is household q's integrated hazard for the duration corresponding to the discrete choice i. η_{iq} is the stochastic error term that takes the extreme value distribution with the cumulative density function given by: $G(\eta) = 1\text{-}exp(\text{-}exp(\eta))$.

Next, in order to specify a non-parametric baseline hazard, the continuous time T, is divided into discrete periods represented by the index k_i (k_i =1,2,3… K_i) for each of i=M, F, and J as:

$$k_i = 1 \text{ if } T \in [0,T_i^1],\ k_i = 2 \text{ if } T \in [T_i^1,T_i^2],\ldots\ k_i = K_i \text{ if } T \in [T_i^{K_i\text{-}1},\infty]$$

Let t_{iq} be the discrete period of termination of duration corresponding to discrete choice i and for household q. Also, define a dichotomous variable, $M_{k_i q}$, such that $M_{k_i q}$ = 1 if household q chooses discrete period k_i (*i.e.,* $t_{iq} = k_i$) for the duration corresponding to discrete choice i, and 0 otherwise. Now, based on the extreme value distribution assumption for the error term η_{iq}, we have:

$$\begin{aligned} &\text{Prob}(M_{k_i q} = 1) = G\left(\delta_{i,k_i} - \gamma_i X_{iq}\right) - G\left(\delta_{i,k_i - 1} - \gamma_i X_{iq}\right), \\ &\text{where, } \delta_{i,k_i} = \ln \Lambda_{0i}(T^{k_i}) \quad \text{and} \quad \delta_{i,k_i - 1} = \ln \Lambda_{0i}(T^{k_i - 1}) \end{aligned} \tag{9}$$

To complete the specification of the model system, define ρ_i as the correlation between υ_{iq}, in the discrete part of the model system and η_{iq}, in the continuous duration part of the model system (for i = M, F, and J).

The likelihood function can be constructed by converting the non-normal error terms into normal random variables (Lee, 1983):

$$\begin{aligned} \upsilon_{iq}^* &= \Phi^{-1}\left[F_i(\upsilon_{iq} \mid \omega_q)\right] \\ \eta_{iq}^* &= \Phi^{-1}\left[G(\eta_{iq})\right] \end{aligned} \tag{10}$$

Using the above-specified transformations, the appropriate joint distributions between the error terms of the discrete and continuous components may be written as:

$$P_2\left[\upsilon_{iq}, \eta_{iq}, \rho_i\right] = \Phi_2\left[\upsilon_{iq}^*, \eta_{iq}^*, \rho_i\right] \; \forall i = M, F, \text{and } J \tag{11}$$

Therefore, from equations (6), (9), and (11), the joint probability that any household q chooses the discrete outcome i (for i = M, F, and J) and a corresponding discrete duration k_i (and conditional on ω_q) is given by:

$$P_q(R_{iq} = 1 \,\&\, M_{k_i q} = 1 \mid \omega_q) = \begin{Bmatrix} \Phi_2\left\{\Phi^{-1}\left(F_i(\beta_i Z_{iq} + \omega_{iq} \mid \omega_q)\right), \Phi^{-1}\left(G(\delta_{i,k_i} - \gamma_i X_{iq}\right), \rho_i\right\} - \\ \Phi_2\left\{\Phi^{-1}\left(F_i(\beta_i Z_{iq} + \omega_{iq} \mid \omega_q)\right), \Phi^{-1}\left(G(\delta_{i,k_i - 1} - \gamma_i X_{iq}\right), \rho_i\right\} \end{Bmatrix} \tag{12}$$

Further, the probability that household q chooses not to shop (*i.e.,* i = N) conditional on ω_q, is given by:

$$P_q(R_{Nq} = 1 \mid \omega_q) = \frac{\exp(\beta_N Z_{Nq} + \omega_{Nq})}{\sum_{l = N, M, F, J} \exp(\beta_l Z_{lq} + \omega_{lq})} \tag{13}$$

Therefore, the conditional likelihood function for household q is:

$$L_q \mid \omega_q = \left[P_q(R_{Nq}=1 \mid \omega_q)\right]^{R_{Nq}} \prod_{i=M,F,J} \left[\prod_{k_i=1}^{K_i} \left[P_q(R_{iq}=1; M_{k_iq}=1 \mid \omega_q)\right]^{M_{k_iq}} \right]^{R_{iq}} \quad \textbf{(14)}$$

The unconditional likelihood function can then be obtained by integrating over the elements in the vector ω_q:

$$L_q = \int_{\omega_q} (L_q \mid \omega_q) f(\omega_q) d\omega_q, \quad \textbf{(15)}$$

where $f(\omega_q)$ is the density function of the multivariate normal distribution function with a mean vector of zero and covariance matrix Σ.

The parameters to be estimated are β_i (for i= N, M, F, and J; the vectors of coefficients on the exogenous variables for the discrete choice), γ_i (for i = M, F, and J; the vectors of coefficients on the exogenous variables for each of the hazard-duration models), $\delta_{i,ki}$ (for i = M, F, and J and k_i =1,2,3… K_i; the parameters defining the baseline hazards), ρ_i, (for i = M, F, and J; the correlation terms), and Σ, (the elements of the covariance matrix). Note that it is not possible to identify all the elements in the covariance matrix, Σ. Hence, it is required to pre-specify the structure of the covariance matrix that is estimatable and also appropriate for describing the problem.

The computation of the likelihood function in equation (15) involves the estimation of a multi-dimensional integral. In this research, we use a Quasi Monte Carlo (QMC) simulation methodology to evaluate this multi-dimensional integral. The conditional likelihood function from equation (14) is computed for different realizations of ω_q drawn from a multivariate normal distribution function (*f*) and averaged to obtain an approximation of the unconditional likelihood function value. To draw the realizations of ω_q from their multivariate normal distribution function (*f*), we use the Halton sequence. The Halton sequence is a QMC sequence that belongs to the r-*adic* expansion of integers (see Bhat 2001a). In one dimension, the Halton sequence corresponding to a prime number, *r*, is generated by expanding the sequence of integers (1,2,3,4,..) in terms of the base *r*. Specifically, the n^{th} element of this sequence, $\varphi_r(n)$,is determined as $\varphi_r(n) = \sum_{l=0}^{L} b_l r^{-l-1}$, where, $b_L b_{L-1} b_{L-2} .....b_2 b_1 b_0$ represents the digitized form of the number n in base r (*i.e.,* $n = \sum_{l=0}^{L} b_l r^l$, where, $0 \le b_l \le r-1$ and $r^L \le n < r^{L+1}$). One can observe that the first *r-1* terms of the Halton sequence corresponding to the prime number *r*, represent the points that divide the unit interval [0,1] into *r* equal intervals (*i.e.*, 1/r, 2/r, 3/r,..). Subsequent terms in the sequence represent the points that divide each of the *r* intervals further into *r* equal parts, points that divide each of the resulting r^2 intervals further into *r* equal parts, and so on. For additional details on the Halton sequence, the reader is referred to Train, 2000, Bhat 2001a, and Bhat 2003b.

The reader will also note that the Halton sequence represents points that *uniformly* cover the unit interval [0,1]. The Halton points for the standard normal distribution can be obtained using the inversion technique as: $\varphi_r^{normal}(n) = \Phi^{-1}(\varphi_r(n))$. Finally, K independent univariate Halton draws can be obtained by pairing the one-dimensional sequences obtained for the first K primes. Multivariate draws with the appropriate covariance structure are then obtained by multiplying the independent univariate draws by the Cholesky decomposition of the covariance matrix.

The parameters are estimated using the maximum (log) simulated likelihood (MSL) estimation procedure using 150 draws of the Halton sequence.

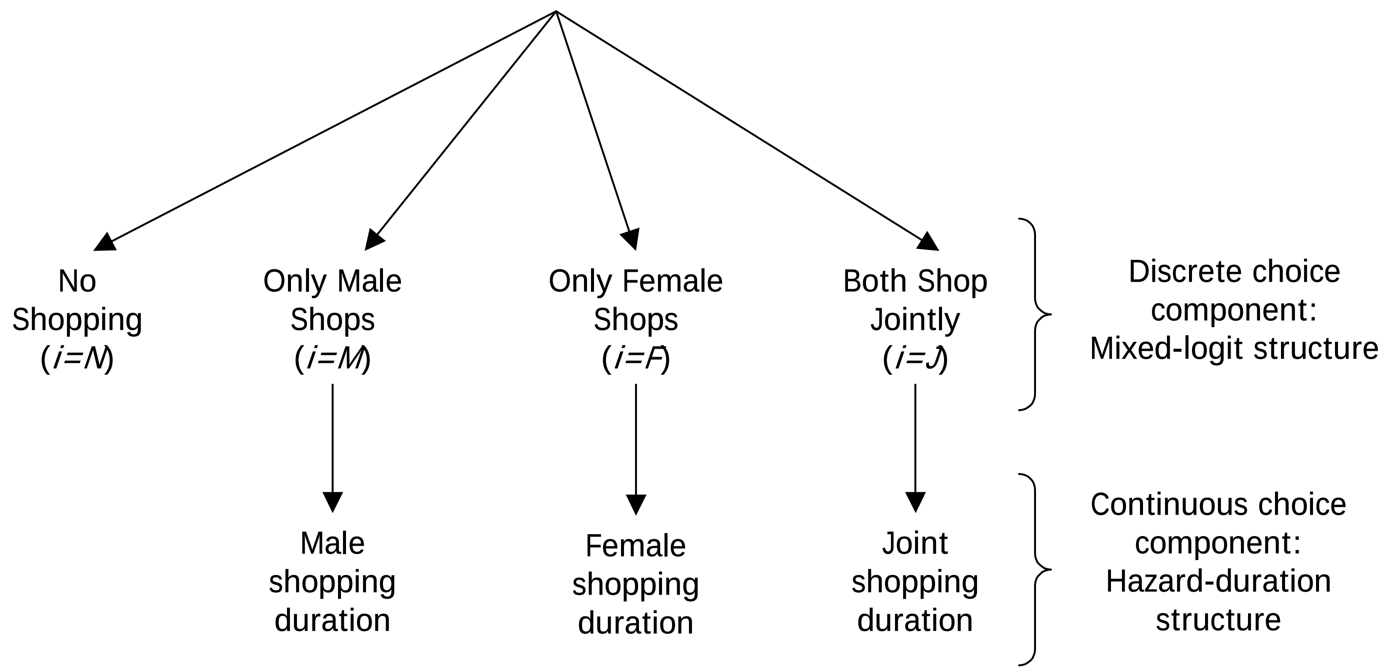

Figure 4.1 Discrete-Continuous Choice Structure for Modeling Out-of-Home Maintenance Activity Generation

4.4 Multiple Discrete-Continuous Model System

The discretionary activity generation involves the joint modeling of the following five discrete-continuous choices: (1) the male's decision to undertake independent in-home discretionary activities and the corresponding duration, (2) the female's decision to undertake independent in-home discretionary activities and the corresponding duration, (3) the male's decision to undertake independent out-of-home discretionary activities and the corresponding duration, (4) the female's decision to undertake independent out-of-home discretionary activities and the corresponding duration, and (5) the household's decision to undertake joint discretionary activities and the corresponding duration. The discrete components of the choices (*i.e.,* the decision to undertake activity) are each modeled using the binary-logit structure. The continuous components of the choices (*i.e.,* the activity duration) are each modeled using a linear regression structure with the natural logarithm of the corresponding activity duration as the choice variable. The binary-logit and the linear-regression models corresponding to each of the five discrete-continuous choices are estimated jointly. Further, correlations among the error terms in the five discrete components are specified to introduce linkages among the discrete-continuous models. Thus, the discretionary activity generation model involves the simultaneous estimation of five discrete-continuous models.

Let i represent the index for the five discrete-continuous choices, which can be one of the following: (1) male's independent in-home choices (i=*MIH*), (2) female's independent in-home choices (i=*FIH*), (3) male's independent out-of-home choices (i=*MOH*), (4) female's independent out-of-home choices (i=*FOH*), (4) household's joint out-of-home choices (i=*JOH*).

The utility functions for the discrete component of the choices is specified as:

$$U_{iq} = \beta_i Z_{iq} + \omega_{iq} - \varepsilon_{iq}, \qquad \textbf{(16)}$$

where, U_{iq} is the indirect utility that household q derives from undertaking activity corresponding to type i. For example, U_{MIHq} is the utility derived from the male undertaking in-home discretionary activities, U_{FIHq} is the utility derived from the female undertaking in-home discretionary activities, etc. Further, we assume that the utility derived from *not* undertaking activities is zero. Z_{iq} is the vector of exogenous variables for household q and alternative i, and β_i is the vector of coefficients on exogenous variables (for alternative i). ω_{iq} and ε_{iq} are stochastic error terms. Assume that $\omega_q = [\omega_{MIHq}, \omega_{FIHq}, \omega_{MOHq}, \omega_{FOHq}, \omega_{JOHq}]$ is multivariate normal distributed with a mean vector of zero and covariance matrix Σ. Identification of the parameters in discrete choice models require that the scale of the utility function be fixed. As a consequence, we fix the variance terms (*i.e.*, the diagonal elements) in covariance matrix Σ as 1. Further, ω_q is also assumed to be independently and identically distributed across households.

Conditional on ω_q, ε_{iq} is assumed to be independently and identically logistically distributed across households (this assumption leads to the binary logit structure for each of the discrete choices, conditional on ω_q). Let $F_i(\varepsilon_{iq} \mid \omega_q)$ represent this cumulative density function.

Defining a dichotomous variable R_{iq} such that $R_{iq} = 1$ if household q chooses to undertake activity corresponding to type i and 0 otherwise, the conditional probability (conditional on ω_q) that household q chooses to undertake activity corresponding to type i is given by:

$$\text{Prob}(R_{iq} = 1 \mid \omega_q) = F_i(\beta_i Z_{iq} + \omega_{iq} \mid \omega_q) = \frac{\exp(\beta_i Z_{iq} + \omega_{iq})}{1 + \exp(\beta_i Z_{iq} + \omega_{iq})} \quad \textbf{(17)}$$

The choice of activity duration conditional on the decision of undertaking activities of each of the types (*i.e., i* = MIH, FIH, MOH, FOH, and JOH) is modeled using a linear regression system. This set of five regression equations can be specified as follows:

$$d_{iq} = \theta_i X_{iq} + \eta_{iq}, \quad \textbf{(18)}$$

where, d_{iq} is the natural logarithm of the duration corresponding to activity of type i (for example, d_{MIHq} is the male's independent in-home activity duration, d_{FIHq} is the female's independent in-home activity duration, etc.). X_{iq} is a vector of exogenous variables, and θ_i is the vector of coefficients on these exogenous variables. Assume that the stochastic error terms, η_{iq} are independently and identically normal-distributed across households with mean zero and variance $\sigma_{\eta i}^2$. Further, these error terms are also assumed to be independently distributed across *i*, *i.e.,* the five choices.

Therefore, the probability of choosing activity duration of t_{iq}, corresponding to the activity type *i,* is given by:

$$\text{Prob}\,(d_{iq} = t_{iq}) \;= \phi\left(\frac{t_{iq} - \theta_i X_{iq}}{\sigma_{\eta i}}\right) \quad \textbf{(19)}$$

where, φ is the standard normal probability distribution function.

The likelihood function can be constructed by converting the non-normal error terms in the discrete choice utility expressions (ε_{iq}) into normal random variables (Lee, 1983):

$$\varepsilon_{iq}^* = \Phi^{-1}\left[F_i(\varepsilon_{iq} \mid \omega_q)\right] \quad \textbf{(20)}$$

Next, define ρ_i as the correlation between ε_{iq}^***,** the (transformed) error term in the discrete part of the model system and η_{iq}, the error term in the continuous duration part of the model system (for i = MIH, FIH, MOH, FOH, and JOH). The joint normal distribution between ε_{iq}^* *and* η_{iq} can, therefore, be specified as:

$$\left(\varepsilon_{iq}^*, \eta_{iq}\right) \sim N_2(0,0,1,\sigma_{\eta i}^2, \rho_i) \quad \textbf{(21)}$$

Therefore, from equations (17), (19), and (21), the probability that household q chooses to undertake activity of type i (for i = MIH, FIH, MOH, FOH, and JOH) and a corresponding duration t_{iq} (and conditional on ω_q) is given by:

$$\text{Prob}\,(R_{iq} = 1 \,\&\, d_{iq} = t_{iq} \mid \omega_q) \;= \frac{1}{\sigma_{\eta i}} \Phi(b_{iq}) \phi(g_{iq})$$

where,

$$g_{iq} = \left(\frac{t_{iq} - \theta_i X_{iq}}{\sigma_{\eta i}} \right) \tag{22}$$

$$b_{iq} = \left(\frac{\Phi^{-1}\left(F_i(\beta_i Z_{iq} + \omega_{iq} \mid \omega_q)\right) - \rho_i g_{iq}}{\sqrt{1 - \rho_i^2}} \right)$$

Further, the probability that household q does not undertake activity of type i (for i = MIH, FIH, MOH, FOH, and JOH), conditional on ω_q is given by:

$$\text{Prob}(R_{iq} = 0 \mid \omega_q) \;=\; 1 - F_i(\beta_i Z_{iq} + \omega_{iq} \mid \omega_q) \;= \frac{1}{1 + \exp(\beta_i Z_{iq} + \omega_{iq})} \tag{23}$$

Therefore, from equations (22) and (23), the conditional likelihood function for any activity of type i and household q, is given by:

$$L_{iq} \mid \omega_q = \left[\text{Prob}(R_{iq} = 0 \mid \omega_q)\right]^{1-R_{iq}} \left[\text{Prob}(R_{iq} = 1 \,\&\, d_{iq} = t_{iq} \mid \omega_q)\right]^{R_{iq}} \tag{24}$$

The overall conditional likelihood function for household q is then the product of the likelihood functions for each activity type:

$$L_q \mid \omega_q = \prod_i \left(L_{iq} \mid \omega_q\right) \tag{25}$$

The unconditional likelihood function can now be obtained by integrating over the elements in the vector ω_q:

$$L_q = \int_{\omega_q} (L_q \mid \omega_q).f(\omega_q) d\omega_q \tag{26}$$

Where $f(\omega_q)$ is the density function of the multivariate normal distribution function with a mean vector of zero and covariance matrix Σ.

The parameters to be estimated (for each of i = MIH, FIH, MOH, FOH, and JOH) are β_i (the vectors of coefficients on the exogenous variables in each of the logit models), θ_i (the vectors of coefficients on the exogenous variables for each of the regression models), $\sigma_{\eta i}^2$ (the variance of the error term in the regression models), and ρ_i, (the correlation terms between the error terms in the discrete and continuous choice components). In addition, the off-diagonal elements of the covariance matrix Σ, representing the correlations in the error terms among the five discrete-continuous models, are also estimated.

The computation of the likelihood function in equation (26) involves the estimation of a five-dimensional integral. We use simulation methods to evaluate this multi-dimensional integral. The conditional likelihood function from equation (25) is computed for different realizations of ω_q drawn from a multivariate normal distribution function (f) and averaged to obtain an approximation of the unconditional likelihood function value. The realizations of ω_q can be obtained from their multivariate normal distribution function (f) using Quasi-Monte Carlo techniques. In this research, we use 150 draws of the Halton sequence (Bhat, 2001a). Multivariate draws with the appropriate covariance structure can be obtained by multiplying a vector of independent univariate draws by the Cholesky decomposition of the covariance matrix. The parameters are estimated using the maximum (log) simulated likelihood (MSL) estimation procedure.

4.5 Summary

This chapter presented detailed econometric structures and the estimation procedures for each of the three model components in this research. The seemingly unrelated regressions model structure is well known in econometric literature. However, to our knowledge, this study represents the first applications of the other two structures (*i.e.,* the joint mixed-logit hazard–duration model and the multiple discrete-continuous model system) for modeling discrete-continuous choices. The likelihood functions and the analytical gradients for all the three model components were coded in the GAUSS 6.0 (Aptech Systems, Inc.) programming language. The maximum likelihood estimations were performed using the MAXLIK library of functions.

Chapter 5. Data

5.1 Introduction

This chapter describes the data used in the empirical estimations. The data sources are first presented in Section 5.2. The sample formation procedure is then detailed in Section 5.3. Finally, several descriptive statistics on the sample characteristics are presented in Section 5.4.

5.2 Data Sources

The primary source of data used in this analysis is the 2000 San Francisco Bay Area Travel Survey (BATS 2000). This two-day survey was designed and administered by MORPACE International Inc. for the Bay Area Metropolitan Transportation Commission MORPACE International Inc. (2002) provides detailed information on the survey sampling and administration procedures. The survey collected detailed activity and travel information for all household members from about 15,000 households for a two-day period. The information collected on activity episodes included the type of activity (based on a 17-category classification system), the location type, start and end times of activity participation, and the geographic location of activity participation. Travel episodes were characterized by the mode used, and the start- and end-times of travel. Further, data on individual and household socio-demographics, individual employment related characteristics, household auto ownership, and Internet access and usage were also obtained.

In addition to the data from the travel survey, data on zonal-level land-use and demographics, and transportation level-of-service measures, were obtained from the Metropolitan Transportation Commission (MTC). The land-use and demographics data file provided, for each of the Traffic Analysis Zones (TAZ), information such as employment levels by sector, zonal population, and area type of the zone (core CBD, other CBD, urban, suburban, or rural). The level-of-service file provided measures such as travel times and costs between each zonal pair by both the highway and transit modes, and for the peak and off-peak periods. These secondary data sources were used to construct measures of accessibility for the different zones. In addition, the level-of service file was also used to determine the no-stop commute duration for persons going to work (See Section 5.2.4 for further details on use of secondary data).

5.2 Sample Formation

The overall process of forming the data sample to be used for the different model estimations comprises the following five steps (Figure 5.1): (1) cleaning and consistency checks, (2) sample extraction, (3) activity-type classification, (4) computation of commute duration and zonal accessibility measures, and (5) aggregation and data structuring. Each of these five steps is described in detail below.

5.2.1 Cleaning and Consistency Checks

The original survey data is available as three main files: (1) the activity data file, (2) the person data file, and the (3) the household data file. The activity data file provides detailed characteristics (such as activity type, location, start and end times, etc.) for each of the activity episodes undertaken by the survey respondents and has information for over 763,000 activity episodes. The person data file has information on the demographic characteristics (for example, gender, age, ethnicity, employment status, etc.) of the survey respondents. The raw person file has information for 34,680 persons. The household file has household-level characteristics such as location of home, tenure, vehicle ownership, etc. for the households responding to the survey. The original household file has information for 15,064 households. These files were screened for missing or inconsistent data. Wherever possible, missing data was imputed and inconsistent data entries fixed. Records for which missing data could not be fixed or inconsistencies not resolved were removed from further analysis.

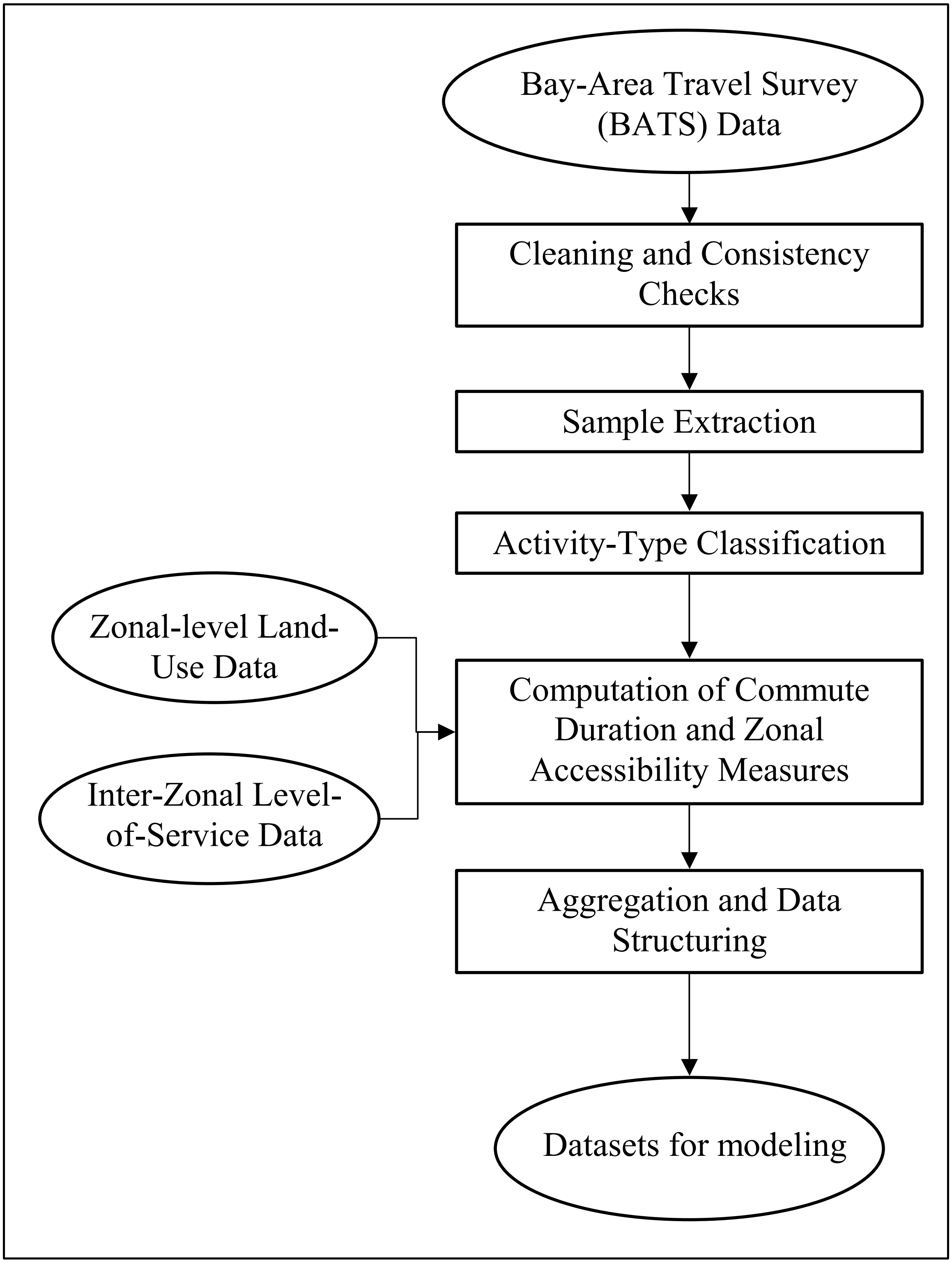

Figure 5.1 Sample Formation Procedure

5.2.2 Sample Extraction

The modeling of household interactions requires complete information on *all* the activities undertaken by *all* household members. Hence, the households for which such complete information was not available were removed from further analysis. Further, since the analysis is focused on a weekday and active, nuclear family, households, the appropriate subset of data was extracted from the overall cleaned data.

5.2.3 Activity-Type Classification

In this step, the activity episodes were first classified into in-home or out-of-home episodes based on the location of activity participation. The survey instrument used a 17-category activity type classification scheme: In addition, the respondents were also asked to provide the location type information (such as Albertson's, Shopping Mall, etc.). Using both the disaggregate activity type classification and the location type information, each of these in-home and out-of-home episodes was classified into one of mandatory, maintenance, or discretionary activities. This procedure is described in detail next.

Within the class of in-home activities, work episodes were classified as mandatory, while episodes described as "household chores and personal care" were classified as maintenance activities. All non-sleep, non-work, and non-chore activities undertaken in-home were classified as in-home discretionary activities. Hence, discretionary activities comprise episodes for purposes such as "recreation/entertainment", "relaxing/resting", "social activities" and "non-work, non-shopping Internet use", etc.

Out-of-home work episodes undertaken by employed adults were classified as mandatory activities. Further, in households with school-going children, the serve-passenger activity episodes of the parents were matched with the school activity episodes of the children to identify the serve-child (*i.e.,* activities undertaken by parents to escort their children to/from school) activity choices of the parents. These activities were also classified as mandatory activities. Grocery shopping was identified as the only out-of-home household maintenance activity. The 17-category activity classification scheme employed by the survey does not distinguish between grocery and non-grocery shopping; however, the activity classification along with information on the location type was used to distinguish grocery-shopping episodes from non-grocery shopping episodes. All other out-of-home activity purposes (*i.e.,* other than work, serve child, and grocery shopping) were classified as out-of-home discretionary activities. Thus, out-of-home episodes for “non-maintenance shopping”, “meals”, “recreation/entertainment”, “personal services”, “social activities”, “appointments” and “volunteer work” were classified into the aggregate class of out-of-home discretionary activities.

In the next step of activity-type classification, the out-of-home maintenance and discretionary episodes were further classified into solo and joint activity episodes. The survey data does not explicitly provide information on whether the activity episodes were undertaken independently or jointly by the household members. Hence, the joint-activity episodes were identified by matching the activity records of the household adults (for the purposes of this study, joint activity episodes refer to only out-of-home activity undertaken jointly by the two households adults; activities undertaken by an adult along with children are not treated as joint). A computer program (in C++) was written to compare activity attributes such as the activity type, start and end times of the episode, and the spatial location of the activity (in terms of latitude and longitude). As reported earlier by Gliebe and Koppelman (2003), this procedure of matching to identify joint activity episodes is complicated by differences in the reporting of activity purposes and the activity start- and end-times and between the two adults. In the current analysis, we enforced the condition that the reported activity types be the same for an episode to be classified as being undertaken jointly. In matching the start- and end-times, however, a tolerance of up to 10-minute differences was allowed in the times reported by the male and female heads. Thus the operational definition of joint activity episodes may be stated as "An out-of-home episode undertaken by the male is defined to be jointly undertaken with another out-of-home activity episode of the female if the reported activity purpose (on the original 17 category classification scheme employed by the survey instrument) is the same, the two activities are undertaken at the exact spatial location (defined by the latitude and longitude) and the activity start and end times reported by the two adults for their respective episodes do not differ by more than 10 minutes". It is also to be noted here that the joint activities as defined above does not necessarily require joint travel to or from the joint episode. It is interesting to note here that despite allowing for a temporal tolerance, about 90% of the joint activity episodes identified matched exactly in both their start and end times. Another 8% of the episodes matched exactly in either the start or the end times. Both the start- and end-times did not match to the minute in only 2% of the cases. Shopping, meals, social activities, and recreational activities were identified as the most common out-of-home activity types undertaken jointly.

At the end of this step of activity-type classification, all activity episodes were classified into in-home or out-of-home and further into mandatory, maintenance, or discretionary activity episodes. Further, the out-of-home maintenance and discretionary activity episodes were also classified into solo or joint episodes.

5.2.4 Computation of Commute Duration and Zonal Accessibility Measures

In this step, the data on inter-zonal level-of-service (by time of day) was used to determine the expected no-stop commute duration by auto between the home and work zones for each employed person who went to work. This was computed by summing the in-vehicle travel time between the home and work zones at the start time of work with the travel time between the work and home zones at the end time of work.

Next, the zonal-level land use data and the inter-zonal level-of-service data were used to compute measures of accessibility to different types of activity opportunities from each zone. The Hansen-type accessibility (see for example, Bhat *et al.*, 1999) of zone i to activity opportunity of type k (k = retail employment, service employment, and total employment) is computed as:

$$Access_{i,k} = \frac{1}{N}\sum_{j=1}^{N}\frac{\ln(Empl_{j,k})}{\ln(autoIVTT_{ij})}.$$

where, $Empl_{j,k}$ is the employment level of type k in zone j and $autoIVTT_{ij}$ is the auto in-vehicle travel time between zones i and j. The measures of accessibility to opportunities from the respective home zones were appended to each household record. Also, for employed persons going to work out-of-home, the accessibility measures for their work zones were appended appropriately to the person records.

5.2.5 Aggregation and Data Structuring

In this step, data was aggregated appropriately to the person and the household level to identify the maintenance and discretionary activities participation choices of persons/households and the durations for the activities undertaken. In the case of out-of-home shopping, the activity was predominantly undertaken either independently by one of the household heads or jointly by both. The few cases in which the household undertook joint episodes in addition to solo episodes by one or both of the adults were appropriately re-classified based on the relative shopping durations of the different episodes into one of the three main allocation patterns; *i.e.,* only male shops, only female shops, or both shop jointly. Finally, separate data sets were created with the data appropriately structured for the estimation of each of the three different model components (*i.e.,* in-home maintenance activity generation, out-of-home maintenance activity generation, and discretionary activity generation).

5.3 Sample Description

The final cleaned dataset has information for 5381 households. The activity file for these households provide information for over 75,000 activity episodes undertaken by the household members. About two-thirds of these activity episodes are in-home while the rest are out-of-home. 2192 of the 25,232 out-of-home episodes were identified as joint episodes. The sample provides a good distribution of data over the five working days of the week (19.5% Monday, 23.6% Tuesday, 22% Wednesday, 18.7% Thursday, and 16.2% Friday). Detailed descriptives on the individual and household characteristics, and the mandatory, maintenance, and discretionary activity participation characteristics of the household heads are provided in the next few sections.

5.3.1 Individual and Household Characteristics

The average age of the males in the sample is 45 years and that of the females is 43 years. About 42% of all males and females in the sample are in the age group of 35-50 years. Almost all adults in the sample are licensed to drive. 92% of the male household heads are employed and of these 94% are full-time workers. In contrast only 73% of the female heads are employed and 75% of the employed women are full time workers. Only 8% of the male household heads and 10% of the female heads attend school, and most of these individuals are part-time students.

Almost 88% of the 5381 households in the sample have two or more automobiles; 11% have a single vehicle and less than 1% of the households have no cars. 84% of the households have access to the Internet at home. 76% of the household heads in the final sample own their home and the rest live in rented dwellings. As regards the racial composition, the sample comprises 80% Caucasian, 10% Asians and Pacific Islanders, 5% Hispanics and the rest belonging to other races. About 61% of the households have no children; 14% have one child, 19% have two children, and the rest have three or more children. 35% of the 5381 households are single-worker households and the rest are dual-worker households.

5.3.2 Mandatory Activity Participation Characteristics

As described in the section on sample formation, this study classifies three types of activities as mandatory. These are out-of-home work, in-home work, and serve-child activities undertaken by parents to escort children to and from school. Sample characteristics on participation in each of these three activities are presented in this section.

The descriptive statistics for out-of-home work participation is presented in Table 5.1. As already indicated in the previous section on individual and household characteristics, there are more employed men than women in the sample. Further, more employed men go to work on any day when compared to women. This is perhaps because men are more likely to be full-time workers then women (this hypothesis is also supported by the data). The average work duration for men undertaking out-of-home work is greater than the average work duration of the females. Further, the average expected commute duration of working men is also found to be greater than that for working women.

Table 5.1 Sample Characteristics: Out-of-Home Work Participation

	Male	Female
Number of employed persons	4951	3925
Percentage of employed persons going to work	83.70%	74.60%
Work duration: Mean (minutes)	500.45	463.31
Work duration: Standard Deviation	147.70	147.86
Expected Commute duration: Mean (minutes)	48.36	40.50
Expected Commute duration: Standard Deviation	35.60	31.63

In addition to the work and commute durations, the work start and end times are also of interest. 53% of working men and 63% of working women in the sample start work between 7 and 9 AM. Also, 45% of working men and 49% of working women in the sample end work between 4 and 6 PM.

The in-home work participation characteristics are examined next. 618 (12.5%) of the 4951 employed males undertook in-home work. The average duration of in-home work for these persons is 324 minutes, with a standard deviation of 212.7

minutes. Of these 618 men, 387 (62.6%) persons undertook in-home work in addition to out-of-home work. The rest worked only at home. In the case of women, 480 (12.3%) of the 3925 employed persons undertook in-home work. The average duration of in-home work for these persons is 318 minutes, with a standard deviation of 212.7 minutes. Of these 480 women, 251 (52.3%) persons undertook in-home work in addition to out-of-home work. The rest worked only at home.

The third type of mandatory activity is the serve-child activity undertaken by parents to escort children to and from school. Of the 5381 households in the sample, 2066 households have one or more children. Of these households with children, 802 (39%) households do not have any school going children (*i.e.,* in these households, no child went to school on the survey diary day); 602 households (29%) have one school going child and the rest have two or more school going children. The subsequent descriptive analysis on serve-child activity participation of the parents is restricted to the 1264 households, which have one or more school going children.

Table 5.2 presents the sample descriptives for the serve-child activity participation choices of the parents. This table presents the percentage of the households in which the serve-child responsibility is undertaken by (1) only female, (2) only male, (3) both male and female, and (4) neither male or female. Note that the percentages sum to 100 in each column. In the overall, (i.e., across all the 1264 households with school going children), the table indicates that the mother is clearly the primary person escorting children to and from school. On examining the impact of the employment status of the household heads on serve-child responsibilities, we find that in 61% of the single worker households, the responsibility is undertaken by the woman alone (In most of the single worker households with children, the woman is the non-worker). The men in dual-worker households are found to be more likely to contribute to serve-child activities when compared to men in single worker households. The share of households in which neither parent undertook serve-child activities is also higher in dual-worker households when compared to single-worker households, perhaps due to car-pooling arrangements. Finally, we examine the effect of the number of school-going children on serve-child responsibilities. The table indicates that when multiple school-going children are present in the household, there is a greater likelihood of both parents undertaking pick-up and drop-off activities possibly because of difference in school times and/or school locations of the different children. Also, the probability that neither undertakes pick-up/drop-off activities is less when multiple school-going children are present in the household.

Table 5.2 Sample Characteristics: Serve-Child Activity Participation

Serve-child responsibility	Overall	Employment status of household heads		Number of school-going children	
		Single worker	Dual worker	One	Two or More
Only female	50.24	61.06	44.58	48.01	52.27
Only male	11.87	9.22	13.25	13.29	10.57
Both male and female	14.32	11.52	15.78	10.63	17.67
Neither male nor female	23.58	18.20	26.39	28.07	19.49

5.3.3 Maintenance Activity Participation Characteristics

In Table 5.3, the descriptive statistics for in-home maintenance time investments of the male and female household heads are presented for each of four different types of households (single worker without children, dual worker without children, single worker with one or more children and dual worker with one or more children) and in the overall. This table indicates that, in the overall (*i.e.,* across all households), females spend more time in household chores than the males. Examination of the relative time investments of the husband and wife across the four types of households reveal interesting and intuitive insights. First, the men and women in dual worker households spend lesser time in household chores than their respective counterparts in single worker households. Second, the presence of children in the household significantly increases the wife's in-home time investment. Third, the disparity between the male and female time investments for household maintenance is the maximum in the case of single worker households with one or more children (in about 93% of such households in the sample, the male was the worker) and the minimum in the case of dual worker households without children. Finally, one can also observe that the variations in the in-home time allocation of females across the four household types is much more pronounced than the differences in the males' time investments.

Table 5.3 Descriptive Statistics: In-home Maintenance Activity Participation

	Number of cases	Male		Female	
		Mean	S.D.	Mean	S.D.
Single worker households with no children	1041	313.36	300.61	444.95	320.82
Dual worker households with no children	2274	252.59	238.79	307.86	250.63
Single worker households with one or more children	845	296.78	256.82	597.03	304.37
Dual worker households with one or more children	1221	293.09	240.10	431.24	271.81
All households	5381	280.48	256.11	407.79	296.58

Table 5.4 presents the sample shares for the discrete household shopping choices (*i.e.,* decision to shop and allocation of this task) and the descriptives for the continuous choice of shopping duration when undertaken by the male, female, and jointly by both. This table indicates that about 81% of the households did not undertake shopping (or alternatively, 19% of all households in the sample undertook grocery shopping on the survey weekday). Among the households that undertook shopping, the responsibility was predominantly found to be assigned to one of the household members, with the instances of joint grocery shopping being few. Further, the table indicates that the female head of the household is significantly more likely to undertake shopping when compared to the male head. The duration of grocery shopping was found on an average to be about 31 minutes when undertaken by the male, 37 minutes when undertaken by the females and about 32 minutes when undertaken jointly. It is interesting to note that the standard deviation in the

distribution of the shopping duration across the sample (see last column in Table 1b) is the minimum for joint episodes and the maximum for episodes undertaken by men. This is perhaps because, when household heads undertake shopping jointly, both very short and very long durations are unlikely given the time constraints of the multiple adults. On the other hand, when men undertake shopping, this may be the primary shopping episode for the household (leading to long durations) or a quick stop for a few essentials (leading to short durations).

Table 5.4 Descriptive Statistics: Out-of-home Maintenance Activity Participation

	Decision to Shop and Task Allocation		Duration (minutes)	
	Freq.	%	Mean	S.D
No Shopping	4375	81.3	-	-
Male Shops	305	5.7	30.96	69.91
Female Shops	633	11.8	37.00	41.81
Joint Shopping	68	1.3	32.19	23.46

5.3.4 Discretionary Activity Participation Characteristics

Table 5.5 presents the in-home and out-of-home discretionary activity participation choices of the male and female household heads. Further, descriptive statistics on the daily activity duration is also provided (the statistics are computed for those undertaking the activities). More men in the sample are found to undertake in-home discretionary activities when compared to women. In contrast, more women are found to undertake out-of-home discretionary activities when compared to men. Adults in about 11% of the sample undertook joint out-of-home discretionary activities. The average in-home discretionary activity durations for both men and women are found to be significantly greater than the corresponding out-of-home durations. The daily average duration spent in joint discretionary activities is found to be comparable to that spent in independent out-of-home discretionary activities.

Table 5.5 Frequency and Duration of Discretionary Activity Participation

	Undertaking activity		Activity duration (minutes)	
	Freq.	%	Average	S.D.
Male in-home	3134	58.24	291.95	215.32
Female in-home	2718	50.51	290.82	221.38
Male out-of-home	2259	41.98	102.74	126.53
Female out-of-home	2659	49.41	115.05	121.25
Joint out-of-home	579	10.76	102.63	88.33

Next, we examine the relative choices of the male and female heads of the households regarding in-home and out-of-home independent discretionary activity participation (Table 5.6). The table indicates that, in about 33% of the households, only one of the household heads undertakes in-home discretionary activities. In contrast, in a vast majority (67%) of the households, either both undertake in-home discretionary activities or neither undertakes such activities. This might be reflective of availability of activity opportunities at home motivating both to undertake discretionary activities in-home, or alternatively, common life-style choices and household constraints preventing both from undertaking in-home discretionary activities. A similar trend, as in the case of in-home activity participation, is also found in the case of out of home discretionary activity participation choices of the household heads. In 60% of the households, either both undertook out-of-home discretionary activities or neither undertook such activities. Thus, this table suggests the possibility of complementary linkages in the discretionary activity participation choices of the household heads.

Table 5.6 Relative Choices of the Male and Female Heads on Independent Discretionary Activity Participation

	In-home		Out-of-home	
	Freq.	%	Freq.	%
Only male undertakes activity	1101	20.46	879	16.34
Only female undertakes activity	685	12.73	1279	23.77
Both undertake activity	2033	37.78	1380	25.65
Neither undertakes activity	1562	29.03	1843	34.25

Finally, we examine the trade-offs between in-home and out-of-home discretionary activity participation choices of household heads (Table 5.7). Specifically, we compare the trade-offs in households not undertaking joint discretionary activities with trade-offs in households undertaking joint discretionary activities. The table indicates that household heads who undertake joint discretionary activities are also more likely to undertake both in-home and out-of-home independent discretionary activities (see entries along the third row). In contrast, men and women who do not undertake joint discretionary activities are also more likely to not undertake any independent discretionary activities (either in-home or out-of-home; see entries along the fourth row) at all. This possibly suggests that adults who pursue joint activities are also in general more active in pursuit of independent discretionary activities.

Table 5.7 Trade-offs Between In-home and Out-of-Home Independent Discretionary Activity Participation Choices

	Households not undertaking joint discretionary activities				Households undertaking joint discretionary activities			
	Male		Female		Male		Female	
	Freq.	%	Freq.	%	Freq.	%	Freq.	%
Only in-home	1593	33.17	1191	24.80	187	32.30	162	27.98
Only out-of-home	785	16.35	1179	24.55	120	20.73	115	19.86
Both in-home and out-of-home	1185	24.68	1181	24.59	169	29.19	184	31.78
Neither in-home nor out-of-home	1239	25.80	1251	26.05	103	17.79	118	20.38
Total	4802	100.00	4802	100.00	579	100.00	579	100.00

5.4 Summary

This research uses the BATS 2000 as the primary data for empirical model estimations. In addition, supplementary data on zonal land-use and inter-zonal transportation level-of-service is also used. The survey data was subject to substantial processing, especially with regards to activity classification and joint activity identification. Details of this processing were presented in this chapter. Further, sample characteristics were also discussed by providing several descriptive statistics.

Chapter 6 Empirical Results: In-Home Maintenance Activity Generation

6.1 Introduction

This chapter presents the empirical results for the generation of in-home maintenance activities. The duration of time (the natural logarithm of duration is used as the dependent variable) invested by the male and female heads in household maintenance tasks is modeled jointly using a system of seemingly unrelated regressions. For this analysis, we segment the sample into the following four groups: (1) single-worker households without children, (2) dual-worker households without children, (3) single-worker households with one or more children, and (4) dual-worker households with one or more children. Separate models are estimated for each of these four segments. The empirical model results for models for single- and dual-worker households without children are presented in Section 6.2 and the models for households with children are presented in Section 6.3.

6.2 Models for Single- and Dual-Worker Households Without Children

The models for in-home maintenance activity generation for single- and dual-worker household without children are presented in Table 6.1. The explanatory variables are classified into household characteristics, individual characteristics, mandatory activity participation characteristics, and day-of-the week variables.

Husbands in dual-worker Caucasian families are found to spend more time undertaking household chores when compared to husbands in Asian, Hispanic, or other types of families. Adults in dual-worker households who own their home are found to spend more time in household chores than those who live in rented dwellings. This is perhaps because of the additional time investments for the general upkeep of one's own home (for example, mowing the lawn) when compared to a rented apartment. Female heads in single-worker households with access to the

Internet from home are found to invest more time in chores than those who live in households without Internet access.

Younger adults (age 16-35) are found to invest lesser time performing in-home maintenance tasks, when compared to older adults, perhaps reflecting a greater overall out-of-home orientation of the younger adults. Further, elder persons may quite naturally, due to physical reasons, require more time for undertaking household chores. Full-time employees are estimated to spend less time in household chores (when compared to part-time employees and unemployed persons in the case of single-worker household and in comparison to part-time employees in the case of dual-worker households), presumably due to time constraints imposed by the work activity. Similarly, adults in dual-worker households who are students are found to spend lesser time in household chores than those who are not students.

The time invested in in-home work during the day negatively impacts the time investment of both the male and female heads in household chores. In the case of females in dual-worker households, the rate of decrease of in-home maintenance duration with increase in in-home work time is found to be much less for in-home work durations less than four hours when compared to in-home work durations between four and eight hours. Specifically, for each additional log-minute of in-home work time between 0 and 4 hours, the logarithm of in-home maintenance time decreases by 0.162 (computed as -0.204+1.310-1.268 = -0.162) while the corresponding number for in-home work duration between 4 and 8 hours is 1.472 (computed as: -0.204-1.268 = -1.472). In the case of single-worker households, the out-of-home work duration is found to negatively impact the in-home maintenance time investment of only the husband. This result, along with the stronger negative impact of the full-time employee variable for the male compared to the female, indicates that, employed women in single-worker households without children, share a higher responsibility in household chores than employed men in similar households even if the durations spent at work are the same. In the case of dual-worker households, the out-of-home work duration has a negative impact on the in-home duration for household chores for both men and women. The commute duration is found to negatively impact the in-home time investment only for males in single-worker households.

The wife's in-home maintenance duration is positively impacted by the out-of-home work duration of her spouse (The husband's in-home maintenance duration, however, is not affected by his wife's out-of-home work duration.). This result, along with the direct negative effect of the male's work duration on his in-home time, suggests that the longer the husband spends at work, greater is the disparity in the maintenance time investments for household chores between the household heads (especially for single-worker households).

Finally, among the different days of the week, females in dual worker households are found to spend more time in household chores during the mid-week (Tuesdays and Wednesdays). The standard deviation of the error term is found to be greater for the males when compared to the females suggesting greater random variations in the male's time investments for household chores when compared to the female's time investment. The correlation between the error terms was estimated to be positive. This indicates that unobserved factors about a household (such as perhaps life style, habits, in-home orientation etc.) that positively impact the in-home duration of the male also positively impact the in-home time investment of the female.

Table 6.1 Model for In-home Maintenance Activity Generation in Single- and Dual-Worker Households Without Children

	Single Worker Household				Dual Worker Household			
	Male		Female		Male		Female	
	Param.	t stat	Param.	t stat	Param.	t stat	Param.	t stat
Household characteristics								
Caucasian	-	-	-	-	0.182	1.956	-	-
Own household	-	-	-	-	0.256	2.744	0.180	2.252
Access to Internet at home	-	-	0.339	2.739	-	-	-	-
Individual characteristics								
Age 16-35 years	-0.274	-1.643	-0.577	-4.038	-0.206	-2.267	-0.318	-4.220
Full-time employee*	-0.452	-2.309	-0.395	-2.570	-0.294	-2.091	-0.331	-3.947
Student	-	-	-	-	-0.295	-2.326	-0.252	-2.504
Mandatory activity participation characteristics								
In-home work duration								
Ln(IH work dur)	-0.214	-5.755	-0.162	-3.387	-0.134	-7.108	-0.204	-6.502
Ln(IH work dur) * IH work dur <= 4 hours	-	-	-	-	-	-	1.310	2.042
Ln(IH work dur) * IH work dur <= 8 hours	-	-	-	-	-	-	-1.268	-2.057
IH work dur <= 4 hours	-	-	-	-	-	-	-7.175	-1.940
IH work dur <= 8 hours	-	-	-	-	-	-	7.778	2.161
Out-of-home work and commute duration								
Ln(OH work dur)	-0.121	-3.152	-	-	-	-	-0.075	-5.401
Work duration > 8 hours	-	-	-	-	-0.212	-2.628	-	-
Commute duration > 60 minutes	-0.311	-1.755	-	-	-	-	-	-
Spouse's out-of-home work duration								
Ln(OH work dur)	-	-	0.043	1.992	-	-	0.046	3.369
Day of the week								
Tuesday	-	-	-	-	-	-	0.143	1.913
Wednesday	-	-	-	-	-	-	0.141	1.837
Constant	5.426	58.850	5.270	37.912	4.736	26.413	5.503	43.241
S.D. of the error term	1.920	45.621	1.720	45.619	1.792	67.415	1.541	67.407
Correlation (t stat)	0.2129 (7.276)				0.3366(18.036)			
Log-likelihood at Convergance	-4173.22 (1041 cases)				-8626.692 (2274 cases)			
Log-likelihood for Constants only Model	-4283.20 (1041 cases)				-8881.789 (2274 cases)			
Adjusted Likelihood Ratio Index	0.023				0.027			

*The base is both part-time and non-employed in the case of single worker households and part-time employee in the case of dual worker households

6.3 Models for Single- and Dual-Worker Households With One or More Children

The models for in-home maintenance activity generation for single- and dual-worker household with one or more children are presented in Table 6.2. The explanatory variables are classified into household characteristics, individual characteristics, and mandatory activity participation characteristics.

Caucasian males in single-worker households are found to spend longer time in in-home chores when compared to men of other ethnicities. The number of children in the household positively impacts the wife's in-home maintenance duration in dual-worker households. In the case of single-worker households, the age composition of the children in the household has a significant impact on the wife's in-home time investment for chores. Specifically, women spend the least amount of time in household chores when all the children are greater than 5 years of age, more time when all the children are younger than 5 years of age (presumably because younger children need more care and attention than older ones) and the most time when both young and old children are present (the base alternative). This high time investment corresponding to the base alternative could be because of the differences in the needs of the young and old children. Neither the number nor the age composition of the children in the household was found to have a significant impact on the male's in-home time investments.

Several individual-level characteristics are found to impact in-home maintenance time allocation of adults in dual-worker households. Younger men (age <= 35 years), adults who are full-time employees, and women who are students are found to invest lesser time in household chores. In contrast, women who have access to their own personal vehicle spend more time in household chores than those who do not. Perhaps, women without a personal vehicle have to rely on transit or other means to commute, thereby decreasing the time available for household chores.

Among the mandatory activity participation characteristics, both the in-home and out-of-home work durations of a person negatively impact his/her in-home maintenance activity duration. The commute duration negatively and non-linearly impacts the husband's in-home maintenance time investment in single-worker households with children. Further, the time allocations of the household adults for household chores are positively impacted by the out-of-home work duration of their spouse in both single and dual worker households, perhaps as a consequence of the presence of children at home who require care and supervision by either of the parents. This effect is unlike in the case of households without children in which the husband's in-home time investment was not impacted by the wife's work duration. Finally, adults who drop-off or pick-up their child(ren) at/from school are also found to invest more time in household chores than those who do not (except females in single-worker households).

As in the case of households without children, the standard deviation of the error term is found to be greater for the males when compared to the females in both single and dual worker households. Further, these standard deviations are lesser when compared to the corresponding values for the households without children suggesting more random variations in in-home maintenance time investments when no children are present in the household. The correlation between the error terms is again estimated to be positive.

6.4 Summary

This chapter presented the empirical models results for the in-home maintenance activity generation. The results indicate that the daily out-of-home work durations of the spouses are very important descriptors of their in-home maintenance time investments. In households without children, the male's out-of-home work duration determines the extent of the disparity in the time invested by the male and female in household chores. In dual-worker households with children, the personal work duration negatively impacts the in-home maintenance time allocation of a person but positively impacts the corresponding duration of the spouse, reflecting a "compensating" effect.

Table 6.2 Model for In-home Maintenance Activity Generation in Single- and Dual-Worker Households With One or More Children

	Single Worker Household				Dual Worker Household			
	Male		Female		Male		Female	
	Param.	t stat	Param.	t stat	Param.	t stat	Param.	t stat
Household characteristics								
Caucasian	0.265	2.020	-	-	-	-	-	-
Number of children								
One child	-	-	-	-	-	-	-0.265	-2.258
Two children	-	-	-	-	-	-	-0.195	-1.717
Age composition of children								
Only young (age <= 4 years) child(ren)	-	-	-0.182	-1.665	-	-	-	-
Only older (age 5-15 years) child(ren)	-	-	-0.195	-1.822	-	-	-	-
Individual characteristics								
Age 16-35 years	-	-	-	-	-0.461	-4.244	-	-
Full-time employee*	-	-	-	-	-0.535	-1.958	-0.263	-3.220
Student	-	-	-	-	-	-	-0.211	-1.601
Access to a personal vehicle	-	-	-	-	-	-	0.300	2.014
Mandatory activity participation characteristics								
In-home work duration								
Ln(IH work dur)	-0.128	-3.701	-	-	-0.060	-2.111	-0.068	-3.103
Out-of-home work duration								
Ln(OH work dur)	-0.057	-1.910	-0.084	-2.498	-	-	-0.058	-3.974
Work duration > 8 hours	-	-	-	-	-0.191	-1.808	-	-
Commute duration								
Ln(Comm. dur.) * comm. dur. <= 30 mins	1.041	1.597	-	-	-	-	-	-
Ln(Comm. dur.) * comm. dur. <= 60 mins	-1.095	-1.933	-	-	-	-	-	-
Comm. dur. <= 30 mins	-4.041	-1.729	-	-	-	-	-	-
Comm. dur. <= 60 mins	4.330	2.029	-	-	-	-	-	-
Spouse's out-of-home work duration								
Ln(OH work dur)	0.131	2.813	0.064	3.374	0.029	1.706	0.035	2.128
Serve-passenger activities								
Pick-up/drop-off of child(ren) at/from school	0.412	2.181	-	-	0.363	3.126	0.223	2.967
Constant	4.891	26.305	5.903	46.285	5.396	19.257	5.743	28.751
S.D. of the error term	1.688	41.081	1.275	41.103	1.669	49.397	1.305	49.399
Correlation (t stat)	0.2449 (7.521)				0.3188 (12.352)			
Log-likelihood at Convergance	-3019.43 (845 cases)				-4350.692 (1221 cases)			
Log-likelihood for Constants only Model	-3091.51 (845 cases)				-4478.04 (1221 cases)			
Adjusted Likelihood Ratio Index	0.019				0.025			

*The base is both part-time and non-employed in the case of single worker households and part-time employee in the case of dual worker households

Chapter 7 Empirical Results: Out-of-Home Maintenance Activity Generation

7.1 Introduction

This chapter discusses the empirical model results for the out-of-home maintenance activity generation. As already indicated, the out-of-home maintenance activity participation choices are modeled using a joint mixed-logit hazard duration model system. We explored different specifications for the structure of the error-covariance (Σ) among the discrete choice alternatives. However, there was no statistical evidence for the presence of correlations or hetroskedasticity in the vector of error terms ω_q. Subsequently, we also explored different nested structures for the discrete choice alternatives (*i.e.,* correlations among the error terms ε_{Nq} , ε_{Mq} , ε_{Fq} , *and* ε_{Jq}). Again, there was no statistical evidence for a nested structure. Therefore, we chose to specify a simple multinomial logit structure for the discrete component of the model. Hence, the overall model structure reduces to a joint MNL-hazard duration model. For ease in presentation, the results for the discrete (decision to shop and task allocation) and the continuous (shopping duration) components are discussed in separate sections below (Sections 7.2 and 7.3 respectively). Section 7.4 presents and interprets the estimated correlations between the discrete and continuous components.

7.2 Discrete Component: Decision to Shop and Task Allocation

The exogenous variables impacting the choice of undertaking shopping and the allocation of this task to one or both of the household heads (Table 7.1) are broadly classified into four categories: (1) household-level characteristics, (2) person-level characteristics, (3) mandatory activity participation characteristics, and (4) in-home maintenance time investment characteristics.

Young households (age of elder adult <= 35 years) are found to be least likely to undertake shopping (as indicated by the positive coefficient for "no-shopping"), whereas elderly households (age of the elder adult > 50 years of age; the base alternative) are most likely to undertake shopping. This is perhaps reflective of overall time constraints faced by younger adults who may be involved in various kinds of activities during the weekday. Households without any cars are found to be more likely to undertake shopping on any weekday (as indicated by the negative coefficient for "no-shopping"). These households may have to undertake frequent trips to the grocery store, as they do not have the means to transport groceries in bulk. Households with few autos (number of cars < number of licensed drivers) are found to be very likely to undertake joint shopping. Among the other household-level characteristics, Caucasians are found to be more likely to undertake shopping during weekdays. Households without children and low-income households (income <= $ 60K) are found to be more likely to undertake joint shopping.

Non-employed males are found to be more likely to undertake grocery shopping compared to employed males. Females who are have access to their own vehicle (*i.e.,* the female is licensed and there are at least as many vehicles in the household as there are licensed drivers) are more likely to undertake the grocery shopping for the household compared to women who do not have their own vehicle. In the latter case of women without a personal vehicle, perhaps the shopping is undertaken jointly (as also indicated by positive coefficient on the variable "few autos"). Alternatively, it is also possible that shopping is undertaken during weekend days when the vehicle is readily available for non-work use.

The mandatory activities to be performed during the day are found to have a very strong influence on choices relating to undertaking grocery shopping during the day. Employed men and women go to work are found not to prefer shopping. This negative effect is found to be stronger for the women than the men. In addition, the longer the person spends at work, the less likely is he/she to undertake grocery shopping during the day. This negative influence of the work duration on the utility for undertaking shopping suggests that shopping activities in the case of dual-worker households may not be pursued on weekdays, but perhaps undertaken on weekend days. Men who commute longer are found to be less likely to undertake shopping. In contrast, the men who undertake serve-child activities to transport their children to/from school are found to be more likely to undertake shopping for the household.

The final set of explanatory variables describes the persons' time investments for in-home maintenance. Men and women who spend less than 2 hours in undertaking in-home maintenance activities are also the ones who are unlikely to shoulder the household shopping responsibilities. This is perhaps reflective of the life-style and habits of these people (for example, being oriented away from household maintenance and possibly more focused on work and/or discretionary activities). This negative influence is found to be stronger for non-employed men than employed men.

The constants indicate the generic bias for the various choice alternatives. The coefficient on joint shopping is significantly smaller than the coefficients on the other alternatives, indicating that joint shopping is generically the least preferred option.

Table 7.1 Model for Out-of-Home Maintenance Activity Generation: Decision to Shop and Task Allocation

	No Shopping		Male Shops		Female Shops		Joint Shopping	
	Param.	t-stat.	Param.	t-stat.	Param.	t-stat.	Param.	t-stat.
HH-level characteristics								
<u>Age</u>								
Young household	0.302	2.996	-	-	-	-	-	-
Middle-aged household	0.155	2.007	-	-	-	-	-	-
<u>Vehicle ownership</u>								
No autos	-1.013	-2.782	-	-	-	-	-	-
Few autos	-	-	-	-	-	-	0.992	3.361
<u>Other variables</u>								
Caucasian	-0.277	-2.957	-	-	-	-	-	-
No children in HH	-	-	-	-	-	-	0.574	1.982
Income <= 60K	-	-	-	-	-	-	0.830	3.289
Person-level characteristics								
Not employed	-	-	0.699	3.243	-	-	-	-
Student	-	-	-	-	-0.215	-1.479	-	-
Has access to personal vehicle	-	-	-	-	0.568	3.601	-	-
Mandatory activity participation characteristics								
<u>Out-of-home work and commute duration</u>								
Person goes out-of-home to work	-	-	-0.392	-1.934	-1.192	-10.150	-	-
Work duration <= 4 hours	-	-	0.757	3.371	0.341	1.835	-	-
Work duration <= 8 hours	-	-	0.329	1.915	0.581	3.980	-	-
Expected no-stop commute duration	-	-	-0.218	-1.554	-	-	-	-
<u>Serve-passenger activities</u>								
Pick-up/drop-off child(ren) from/at school	-	-	0.358	1.642	-	-	-	-
In-home maintenance time investment								
In-home maintenance <= 2 hours	-	-	-0.230	-1.685	-0.451	-3.955	-	-
In-home maintenance <= 2 hours * Not employed	-	-	-0.885	-1.758	-	-	-	-
Constant	-	-	-2.541	-14.435	-2.053	-11.289	-5.078	-17.332

7.3 Continuous Component: Shopping Duration

This section discusses the hazard-duration models for shopping activity duration. The estimated baseline hazards for the male-, female-, and joint-shopping durations are presented in Figure 7.1. This figure also compares the baseline hazards from joint discrete-continuous models with the baseline hazards estimated from independent hazard-duration models. The baseline hazards for male- and joint-shopping durations are identical for both the independent and joint models as the corresponding correlations turned out to be statistically not different from zero. In the case of female shopping duration, the correlation was positive (the correlations are discussed in detail in Section 7.4). The plots indicate that ignoring this positive correlation results in over-estimation of the duration dependence as indicated by the higher hazards rates for female shopping duration from the independent model.

In general, the plots show an upward trend (especially for durations upwards of 20-25 minutes) for the hazard; *i.e.,* the probability that a shopping episode will terminate increases with increase in duration of the activity. This is intuitive given the "focused" nature of grocery shopping pursuits. The duration dependence effect is the strongest for joint shopping, reflective of the time constraints of multiple people involved in the activity. The model also indicates that the duration dependence effects are not as strong in determining the shopping time of women as they are in determining the shopping time of men. This is perhaps because women are often the primary shoppers for the household and hence require a certain minimum amount of time to complete the shopping.

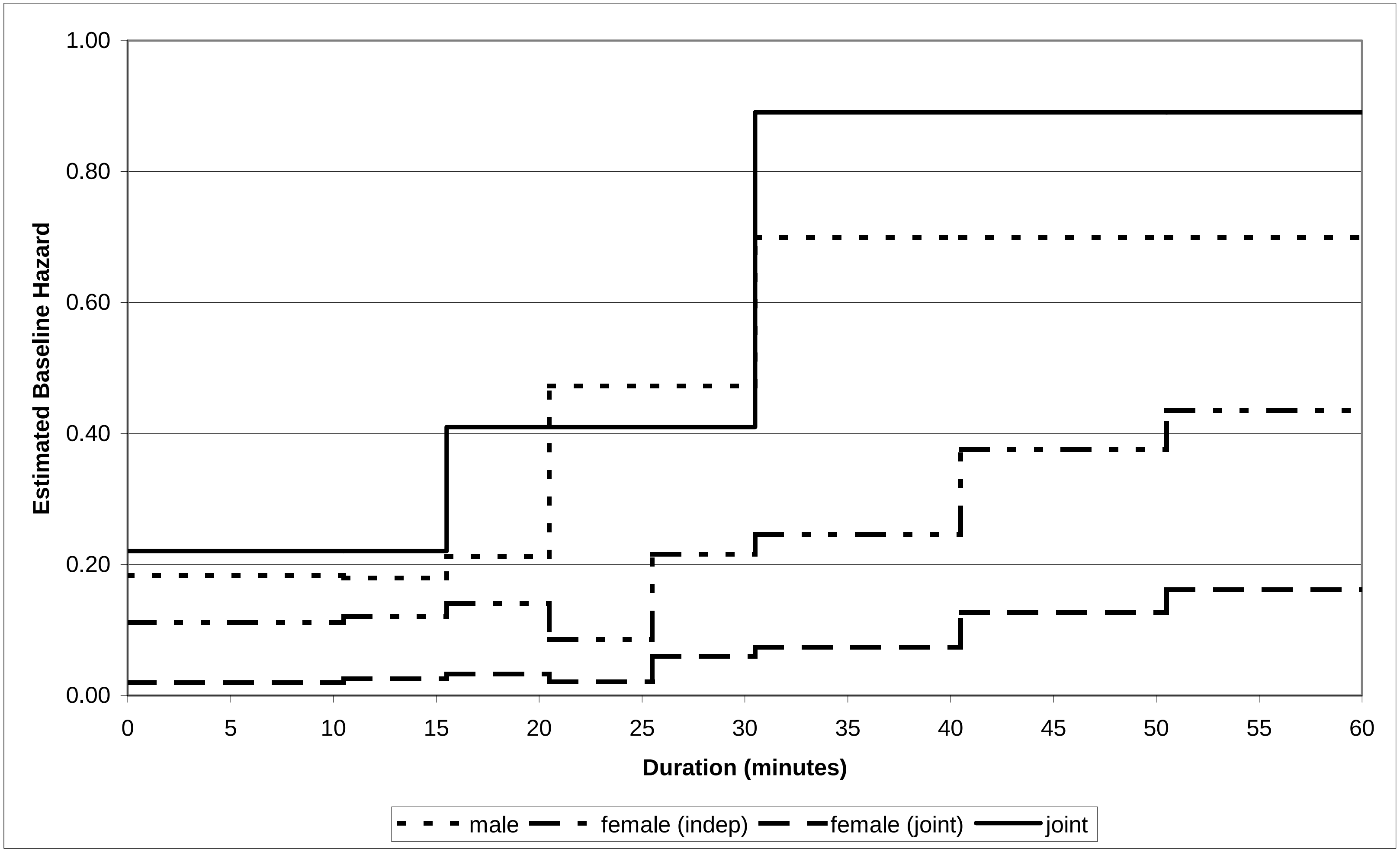

Figure 7.1 Estimated Baseline Hazard for Shopping Duration

The effects of the covariates are presented in Table 7.2. These are classified into four categories: (1) household level characteristics, (2) the mandatory activity participation characteristics for the day, (3) the in-home time investment characteristics for the day and (4) the day-of-the-week effects. Note that as specified in equation (7) in Chapter 3, a negative coefficient implies a higher hazard or equivalently, a lower duration.

Joint-shopping episodes undertaken by adults in households with few vehicles are found to be of shorter duration than those undertaken by adults in households with many vehicles. Perhaps, in the latter case of households with many vehicles, the joint shopping is seen more as family time rather than being motivated by resource constraints and hence leads to longer durations. Further, joint-shopping episodes undertaken by adults and single-worker households and in low-income households (income <= $60K) are found to be of longer durations. The final household-level characteristic impacting shopping duration is the presence of children. When men in households with children undertake shopping, they are found to spend more time in the activity when compared to men in households without children. This is possibly because the men may have to shoulder the primary shopping responsibility with the women having to spend significant time in child-rearing.

The mandatory activity participation characteristics are also found to significantly impact shopping durations. The shopping duration for both males and females is found to be shorter if the person's work ends at 4 PM or later compared to the duration when the person's work ends before 4 PM. Since workers are found to undertake activities predominantly after work (Bhat and Singh, 2000), this result is intuitive as the person has more time to undertake activities, the earlier he/she leaves work. Further, the model also indicates that men, unlike in the case of women, whose work ends between 4 and 6 PM (the peak period) have the shorter shopping durations than even those whose work ends after 6 PM. These results have substantial implications for policy actions like the employer-based demand-management schemes that are aimed at spreading the peak by releasing people earlier from work. In evaluating such schemes the analyst must consider the greater possibility of activity participation (note that the work duration was found to negatively impact the choice of undertaking shopping) and longer durations for the activities undertaken to avoid over predicting the efficiency of the policy action.

The next set of variables in Table 7.2 present the impact of in-home maintenance time investments on shopping durations. Females who spend very long time (10 hours or more) undertaking household chores are found to spend lesser time in shopping reflecting overall time constraints. In the case of men, the in-home time investment was found to impact shopping durations only for those who are not employed. Non-employed males who spend less than 2 hours in household chores are also found to spend lesser time in shopping. Perhaps such unemployed men who do not substantially contribute to in-home household tasks are also only likely to undertake quick supplemental shopping episodes rather than the primary shopping for the household. In contrast, unemployed men who spend between 2 and 10 hours in household chores are found to spend more time in shopping.

The final set of variables capture the impact of the day of the week. The men who undertake shopping on Mondays are found to spend less time when compared to those that undertake shopping on the other weekdays. In the case of women, shopping undertaken during the mid week (Wednesdays) tends to be of shorter durations. Finally, joint shopping when undertaken on a Friday tends to be of a longer duration compared to joint shopping undertaken on other days.

Table 7.2 Model for Out-of-Home Maintenance Activity Generation: Shopping Duration

	Male Shops		Female Shops		Joint Shopping	
	Param.	**t-stat.**	**Param.**	**t-stat.**	**Param.**	**t-stat.**
HH-level characteristics						
Dual worker HH	-	-	-	-	-0.959	-2.846
Few autos	-	-	-	-	-1.007	-2.702
Income <= 60K	-	-	-	-	0.694	2.150
One or more children in HH	0.270	2.061	-	-	-	-
Mandatory activity participation characteristics						
Work ends between 4 and 6 PM	-0.685	-4.658	-0.457	-2.219	-	-
Work ends after 6 PM	-0.500	-2.748	-0.479	-1.870	-	-
In-home maintenance time investment						
In-home maintenance <= 10 hours	-	-	0.240	2.175	-	-
In-home maintenance <= 2 hours * Not employed	-1.028	-1.969	-	-	-	-
In-home maintenance <= 10 hours * Not employed	0.488	1.943	-	-	-	-
Day-of-the-week						
Monday	-0.301	-2.056	-	-	-	-
Wednesday	-	-	-0.207	-1.765	-	-
Friday	-	-	-	-	1.409	3.012
Correlation term	-	-	0.729	6.411	-	-
Log-liklihood at Convergence	-51212.31 (5381 cases)					
Log-liklihood for Constants only Model	-5425.56 (5381 cases)					
Adjusted Likelihood Ratio Index	0.032					

7.4 Correlations between the Discrete and Continuous Components

The correlation between the propensity that a female undertakes shopping and the female's shopping duration hazard (ρ_F) is positive indicating that the unobserved factors that *increase* a woman's propensity to undertake shopping also *decrease* her shopping duration (or alternatively increase the hazard rate). This is perhaps because women, who undertake the shopping for the household, do so on a regular basis and hence are inherently efficient shoppers. The correlations between (1) the male's propensity to shop and the male shopping duration hazard (ρ_M) and (2) the joint shopping propensity and the joint shopping duration hazard (ρ_J) were not found to be statistically significant.

7.5 Summary

This chapter described the empirical models results for the out-of-home maintenance activity generation. The employment status of the male very significantly impacts his propensity to undertake grocery shopping for the household. In the case of women, the need to go to work out-of-home has a strong negative influence on her propensity to undertake the household's shopping. On the other hand, the availability of a personal vehicle has a significant positive influence on the female undertaking shopping for the household. Joint shopping is found to be the generically least preferred option and most likely to be pursued only by households with a single vehicle. The work end time of a worker is found to be a very significant descriptor of independent shopping durations.

Chapter 8 Empirical Results: Discretionary Activity Generation

8.1 Introduction

This chapter discusses the empirical model results for discretionary activity generation. This comprises five discrete-continuous choices estimated simultaneously. For ease in presentation, the five discrete components (decisions to undertake discretionary activities) are presented in Section 8.2. The continuous components (activity duration) and the correlations between each of the discrete and the corresponding continuous components are discussed in Section 8.3. Section 8.4 presents and interprets the matrix of error covariances among the five discrete-continuous components. Empirical and practical considerations required imposing a particular structure to the covariance matrix, Σ. Nonetheless, the estimated multiple discrete-continuous model with this covariance matrix structure was found to be better than independent discrete-continuous models (the log-likelihood value at convergence for the joint model was –27957.20 whereas the corresponding value for independent models was –28189.229).

8.2 Discrete Components: Decisions to Undertake Discretionary Activities

The results for the discrete components (*i.e.,* the decisions to undertake activities) are presented in Table 8.1. The explanatory variables are classified into the following categories: (1) Household characteristics, (2) Individual characteristics, (3) Mandatory activity participation characteristics, (4) In-home maintenance activity participation characteristics, (5) Out-of-home maintenance activity participation characteristics, (6) Spouse's activity participation characteristics, and (7) Day-of-the-week and season variables.

8.2.1 Household Characteristics

The presence of children in the household significantly impacts the discretionary activity participation characteristics of household adults. In particular, the greater the number of younger children (aged 0 to 10 years) in the household, the lesser is the likelihood of the male undertaking out-of-home discretionary activities during the day. On the other hand, the greater the number of older children (aged 11 to 15 years) in the household, the greater is the likelihood of the male participating in in-home discretionary activities. Finally, adults in households with more children are found to be less likely to undertake joint out-of-home discretionary activities during the weekday, as indicated by the negative coefficients on all the three children related variables. The reader will also note that the negative impact of the number of children of school-going age (*i.e.,* 5 years and above) is stronger than that of the number of very young children in the household.

Adults in Caucasian households are found to be more likely to undertake independent out-of-home discretionary activities compared to adults in households of other ethnicity. In contrast, Asian women are found to be less likely to undertake out-of-home discretionary activities compared to women of other ethnicities.

Adults in low-income households are found to be less likely to undertake solo out-of-home discretionary activities. In contrast, adults in households with many bicycles are found to be more likely to undertake independent out-of-home discretionary activities. Possibly, the presence of many bicycles in the household reflects an overall out-of-home orientation of these people. Women living in their own households are more likely to undertake out-of-home discretionary activities. This may be possibly because the neighborhoods in which homes are located may offer more opportunities for out-of-home discretionary activity participation than the neighborhoods in which rental apartments are located. Finally, adults in young households (age of elder member < 35 years) are found to be more likely to undertake joint discretionary activities.

8.2.2 Individual Characteristics

Age, employment status, student status, and personal vehicle availability are the individual characteristics impacting discretionary activity participation decisions.

Younger adults (both male and female) are less likely to undertake in-home discretionary activities when compared to older adults. Similarly, employed adults are also found to be less likely to undertake in-home discretionary activities during the day possibly because of overall time constraints imposed by the work activity. Male students are less likely to undertake out-of-home discretionary activities while female students are less likely to pursue in-home discretionary activities. Finally, availability of a personal vehicle increases the propensity of both the male and the female to undertake independent out-of-home discretionary activities.

8.2.3 Mandatory Activity Participation Characteristics

Next, we examine the impact of mandatory activity participation characteristics on discretionary activity generation decisions. Increasing time investments in in-home work during the day decreases the propensity of the men and women to undertake in-home discretionary activities. On examining the impact of in-home work duration on out-of-home discretionary activities, we find that, among all adults who work in-home, men and women who work for fewer than 4 hours are the most likely to undertake out-of-home discretionary activities. In contrast, men and women working in-home between 4 and 8 hours are unlikely to undertake out-of-home discretionary activities (see the negative coefficient on the variable "IH Work Dur. <= 8 Hours"). Finally, those who work in-home for longer than 8 hours (the base category, with a coefficient of zero) are found to be more likely to undertake solo out-of-home discretionary activities than those working between 4 and 8 hours. Perhaps, a very long time investment in in-home work may motivate out-of-home activities for relaxation. These results suggest that home-based telecommuting can impact the overall discretionary activity participation behavior in different ways depending on the duration spent in in-home work.

Increasing out-of-home work duration decreases the propensity of the adults to undertake in-home and out-of-home discretionary activities, as would be expected. Household adults are found to be less likely to undertake out-of-home discretionary activities jointly, if one or both of them go to work. In addition, the propensity to undertake joint discretionary activities further decreases with increase in work duration of the spouses. These results indicate that compressed workweek programs could result in increased possibilities of joint discretionary activities of the spouses on the day on which the adult does not have to go to work.

The commute duration is also found to decrease the propensity to undertake independent discretionary activities. Further, this negative impact of commute duration is stronger on in-home discretionary activity participation; suggesting that decreasing commute durations of workers is more likely to lead to in-home discretionary activities when compared to out-of-home discretionary activities.

Finally, men who undertake serve-passenger activities to escort their children to/from school are also more likely to undertake out-of-home discretionary activities. In the case of women, undertaking serve-child activities does not significantly impact their independent discretionary activity choices. However, if a woman undertakes serve-child activities, then the household's adults are less likely to participate in discretionary activities jointly.

8.2.4 In-Home Maintenance Activity Participation Characteristics

In the overall, increasing in-home maintenance time investments decreases the propensity of the adults to undertake in-home discretionary activities. Further, certain differences are also observed in this negative impact between employed and non-employed women. Specifically, employed women who spend between 2 and 10 hours in household chores are less likely to undertake in-home discretionary activities compared to unemployed women who spend an equal amount of time in household chores (An employed woman's propensity for undertaking in-home discretionary activities is 2.611 if her in-home maintenance duration is between 2 and 6 hours and 1.250 if her in-home maintenance duration is between 6 an 10 hours. The corresponding numbers for non-employed women are 3.521 and 2.16). Men who spend more than 6 hours and women who spend more than 10 hours in household chores are found to be the less likely to undertake out-of-home discretionary activities indicating a negative impact of in-home maintenance duration on out-of-home discretionary activity participation. Finally, adults in households in which the female spends more than 10 hours in household chores are found to be less likely to undertake joint discretionary activities.

8.2.5 Out-of-Home Maintenance Activity Participation Characteristics

The next set of variables relate to the out-of-home maintenance activity decisions of the household. Men and women, who undertake shopping for the household, are more likely to undertake independent out-of-home discretionary activities during the day. Further, females who shop are also more likely to undertake in-home discretionary activities during the day. Finally, adults undertaking joint shopping are more likely to engage in joint discretionary activities compared to adults not undertaking joint shopping.

8.2.6 Spouse's Activity Participation Characteristics

We now examine the impact of the spouse's mandatory and maintenance activity choices on the independent discretionary activity participation decisions of the household heads. If the wife spends less than 4 hours in in-home work, the husband is found to be more likely to undertake in-home discretionary activities. If the husband spends less than 8 hours in in-home work, the wife is more likely to undertake in-home discretionary activities and less likely to pursue out-of-home activities. Note that the male's in-home work duration between 4 and 8 hours was also found to negatively impact his independent out-of-home discretionary activity participation decision (See Section 8.2.3). This suggests that when the husband works in-home between 4 and 8 hours, perhaps the adults prefer to engage in in-home discretionary activities together and are less likely to undertake out-of-home activities.

The out-of-home work duration of the spouse also impacts the independent out-of-home discretionary activity participation decisions. Specifically, a person is found to be less likely to undertake out-of-home discretionary activities if his/her spouse works for very long durations (*i.e.,* greater than 8 hours). The final variable examines is the impact of the spouse's in-home maintenance time investment. A person is more likely to undertake in-home discretionary activities if his/her spouse spends very little time (of less than 2 hours) in household chores.

In the overall, these empirical results indicate that the daily discretionary activity participation choices of a person are significantly influenced by the characteristics of the work and maintenance activities undertaken by his/her spouse. The implication here is that travel-demand management policy actions, such as flexible work hours, compressed work weeks, and home-based telecommuting which influence the work duration of a person can also impact the in-home and out-of-home discretionary activity participation choices of the spouse, resulting in changes to the overall travel patterns of *both* household adults.

8.2.7 Day of the Week and Season Variables

The final set of variables examined relate to the day of the week and season characteristics. Men and women are found not to prefer mid-week (*i.e.,* Wednesdays) for in-home discretionary activities. Fridays are preferred for joint out-of-home discretionary activities. Men and women are more likely to undertake in-home discretionary activities during summer (June, July, and August). Finally, for reasons not readily apparent, men are found to be less likely to undertake independent discretionary activities during Fall (September, October, and November) and joint activities are found to be less likely in Spring (March, April, and May).

Table 8.1 Model for Discretionary Activity Generation: Decision to Undertake Activities

	Male, IH		Female, IH		Male, OH		Female, OH		Joint, OH	
	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.
Houshold Characteristics										
Presence of Children										
Number of kids aged 0 to 4	-	-	-	-	-0.114	-2.530	-	-	-0.183	-2.533
Number of kids aged 5 to 10	-	-	-	-	-0.131	-2.565	-	-	-0.262	-2.812
Number of kids aged 11 to 15	0.155	1.771	-	-	-	-	-	-	-0.257	-2.220
Ethnicity										
Caucasian	-	-	-	-	0.326	5.184	0.121	1.462	-	-
Asian	-	-	-	-	-	-	-0.435	-3.907	-	-
Other										
Low Income	-	-	-	-	-0.273	-4.507	-0.388	-4.774	-	-
Number of Bicycles	-	-	-	-	0.047	2.586	0.068	3.705	-	-
Own Household	-	-	-	-	-	-	0.250	3.640	-	-
Young Household	-	-	-	-	-	-			0.287	3.217
Individual Characteristics										
Age										
Age 16 to 35 years	-0.644	-6.024	-0.229	-2.856	-	-	-	-	-	-
Age 36 to 50 years	-0.469	-5.024	-	-	-	-	-	-	-	-
Employment Status										
Full-Time Employee	-0.624	-3.811	-0.233	-2.371	-	-	-	-	-	-
Part-Time Employee	-0.624	-3.811	-	-	-	-	-	-	-	-
Student Status										
Full-Time Student	-	-	-0.319	-1.368	-0.309	-3.340	-	-	-	-
Part-Time Student	-	-	-	-	-0.309	-3.340	-	-	-	-
Other Variables										
Personal Vehicle Availability	-	-	-	-	0.357	4.313	0.167	1.892	-	-

Table 8.1 Model for Discretionary Activity Generation: Decision to Undertake Activities (Continued)

	Male, IH		Female, IH		Male, OH		Female, OH		Joint, OH	
	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.
Mandatory Activity Participation Characterisitics										
In-Home Work										
IH Work Dur. <= 4 Hours	-	-	1.082	3.659	0.762	4.539	0.703	3.441	-	-
IH Work Dur. <= 8 Hours	0.746	4.494	-	-	-0.539	-3.601	-0.496	-2.956	-	-
Out-of-Home Work										
OH Work Dur. <= 4 Hours	0.598	2.975	1.096	5.816	-	-	-	-	-	-
OH Work Dur. <= 8 Hours	0.853	7.324	0.586	4.995	1.007	13.937	0.922	10.124	-	-
OH Work Variables (for Joint, OH only)										
Male goes to work	-	-	-	-	-	-	-	-	-0.917	-9.168
Female goes to work	-	-	-	-	-	-	-	-	-0.681	-6.857
Male's OH work duration > 8 hours	-	-	-	-	-	-	-	-	-0.515	-5.515
Female's OH work duration > 4 hours	-	-	-	-	-	-	-	-	-0.445	-2.460
Commute										
LN(Comm. Dur.)	-0.449	-15.333	-0.399	-11.353	-0.265	-13.598	-0.294	-11.718	-	-
Serve-Child										
Male Undertakes Serve-Child Activity	-	-	-	-	0.306	2.320	-	-	-	-
Female Undertakes Serve-Child Activity	-	-	-	-	-	-	-	-	-0.373	-1.761
In-Home Maintenance Activity Participation Characterisitics										
For all Persons										
IH Maint. Dur. <= 2 hours	2.861	24.307	2.379	16.499	-	-	-	-	-	-
IH Maint. Dur. <= 6 hours	1.353	12.031	1.361	12.141	0.191	3.195	-	-	-	-
IH Maint. Dur. <= 10 hours	1.539	11.885	1.250	9.770	-	-	0.379	4.509	-	-
For Non-Employed Persons										
IH Maint. Dur. <= 2 hours	-	-	-1.886	-4.729	-	-	-	-	-	-
IH Maint. Dur. <= 6 hours	-	-	-	-	-	-	-	-	-	-
IH Maint. Dur. <= 10 hours	-	-	0.910	5.430	-	-	-	-	-	-
For Joint, OH only										
Female's IH Maint. Dur. > 10 hours	-	-	-	-	-	-	-	-	-0.594	-4.219

Table 8.1 Model for Discretionary Activity Generation: Decision to Undertake Activities (Continued)

	Male, IH		Female, IH		Male, OH		Female, OH		Joint, OH	
	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.
Out-of-Home Maintenance Activity Participation Characterisitics										
Male Shops	-	-	-	-	0.765	5.513	-	-	-	-
Female Shops	-	-	0.223	1.986	-	-	0.723	6.837	-	-
Joint Shopping	0.485	1.472	-	-	-	-	-0.481	-1.590	2.785	9.550
Spouse's Activity Participation Characteristics										
In-Home Work										
IH Work Dur. <= 4 Hours	0.605	2.247	-	-	-	-	-	-	-	-
IH Work Dur. <= 8 Hours	-	-	0.312	2.146	-	-	-0.291	-2.127	-	-
Out-of-Home Work										
OH Work Dur. <= 8 Hours	-	-	-	-	0.162	2.454	0.158	2.270	-	-
In-Home Maintenance (All Persons)										
IH Maint. Dur. <= 2 hours	0.450	4.254	0.511	6.550	-	-	-	-	-	-
In-Home Maintenance (Non-Empl. Person)										
IH Maint. Dur. <= 10 hours	0.230	1.857	-	-	-	-	-	-	-	-
Day-of the-Week and Season Variables										
Wednesday	-0.197	-2.068	-0.202	-2.242	-	-	-	-	-	-
Friday	-	-	-	-	0.049	0.730	-	-	0.494	4.952
Summer	0.287	3.326	0.188	2.308	-	-	-	-	-	-
Fall	-	-	-	-	-0.102	-1.954	-	-	-	-
Spring	-	-	-	-	-	-	-	-	-0.336	-3.997
Constant	-1.068	-6.740	-1.679	-16.454	-0.595	-5.021	-0.432	-3.256	-2.034	-14.946

8.3 Continuous Components: Activity Durations

The results for the continuous components (*i.e.,* the activity durations) are presented in Table 8.2. The explanatory variables are classified into the following categories: (1) Household characteristics, (2) Individual characteristics, (3) Mandatory activity participation characteristics, (4) In-home maintenance activity participation characteristics, (5) Out-of-home maintenance activity participation characteristics, (6) Spouse's activity participation characteristics, (7) Spatial variables, and (8) Day-of-the-Week Variables. The correlations between the five discrete components and the corresponding continuous components are also described.

8.3.1 Household Characteristics

The household characteristics impacting the duration of discretionary activities are the household income, tenure of the housing unit, and the number of bicycles. Men in low- and medium-income households are found to spend more time in in-home discretionary activities compared to men in higher income (income > $100K) households. Adults in own households spend more time in joint out-of-home discretionary activities than those who live in rental units. Finally, the number of bicycles in the household has a negative impact on the female's in-home discretionary time investment and the positive impact on the joint out-of-home time investments of the household adults.

8.3.2 Individual Characteristics

The employment status and the student status are the individual-level characteristics impacting the duration of discretionary activities. Employed women spend lesser time in in-home discretionary activities, presumably due to time constraints imposed by the work activity. Women who are students spend less time in both in-home and out-of-home discretionary activities when compared to women who are not students. Interestingly, none of these characteristics were found to impact the male's discretionary activity duration choices.

8.3.3 Mandatory Activity Participation Characteristics

Next, we examine the impact of the mandatory activity participation characteristics on discretionary activity duration. Increasing time investments in in-home maintenance duration is found to decrease the person's independent discretionary activity durations, both in-home and out-of-home. Further, the time invested by the female in in-home work also negatively impacts the household's joint discretionary activity duration.

Increasing out-of-home work time investments is also found to decrease solo discretionary activity durations. Further, non-linear spline-type effects were also found in the impact of this out-of-home work duration on discretionary activity duration (except in the case of male's out-of-home duration). Specifically, the rate of decrease of discretionary activity duration with increase in work duration is the maximum for work durations between 4 and 8 hours.

The commute duration has a negative, non-linear impact on the female's in-home discretionary activity duration, with the decrease is in-home discretionary activity duration with increasing commute duration being the maximum for commute durations between 30 and 60 minutes (see the negative coefficient on the variable "LN[Comm. Dur.]*Comm. Dur. <= 60 mins.").

Men who undertake serve-child activities are found to spend lesser time in out-of-home discretionary activities. Such men are also more likely to undertake independent out-of-home discretionary activities (see discussion in Section 8.2.3). Hence, the model suggests that men escorting their children to/from school are likely to undertake short out-of-home discretionary activities. In the case of women, those undertaking serve-child activities are found to spend less time in discretionary activities both in-home and out-of-home. However, if adults in households in which women undertake serve-child episodes undertake joint activities, these are found to be of a longer duration. Note that adults in such households are, in general, less likely to undertake joint activities (see discussion in Section 8.2.3). Perhaps, the joint activity in such cases is undertaken along with the children or alternatively, is undertaken by only the spouses after making suitable arrangements for child-care and hence leads to longer durations. These results are of particular significance in highlighting the ability of the flexible, reduced form based approach for modeling discrete continuous choices to capture differential effects of the same explanatory variable on the discrete and the continuous components of the choices. The reader will note that serve-child related variables discussed here have one effect on the discrete component of the choice and the opposite effect on the continuous component of the choice. Such impacts cannot be captured in Tobit-type models in which the discrete component of the choice is not explicitly modeled.

8.3.4 In-Home Maintenance Activity Participation Characteristics

The in-home maintenance activity duration has an overall negative and non-linear impact on the discretionary activity duration choices of household adults. Further, in the case of females, this impact of the in-home maintenance duration on in-home discretionary activities is found to be different for employed and non-employed persons. Specifically, for lower maintenance durations of 2 to 6 hours, the impact rate (*i.e.,* the rate of decrease in in-home discretionary duration with increasing in-home maintenance duration) for employed women is higher than that for the non-employed women, perhaps because of the greater overall time constraints of the employed persons (the impact rate is 1.034/log-minute for employed women and 0.515/log-minute for non-employed women). In contrast, the impact of increasing maintenance duration on in-home discretionary activity durations is found to be strong for non-employed females only at higher maintenance durations of greater than 6 hours. Specifically, the impact rate for non-employed women is 1.539/log-minute for in-home maintenance durations between 6 and 10 hours and 2.2/log-minute for in-home maintenance durations greater than 10 hours.

In the case of independent, out-of-home discretionary activities, the rate of decrease in discretionary activity durations with increase in in-home maintenance durations is the maximum for in-home maintenance durations greater than 10 hours and significantly lesser for durations less than 10 hours.

Finally, in-home maintenance duration is also found to impact the joint out-of-home discretionary durations. If men undertake in-home chores for more than 6 hours, the duration of the joint activity is found to be shorter. However, women who spend long durations (greater than 10 hours) in household chores are found to undertake joint activities with her spouse for longer durations. Note that adults in households in which women spends a very long time in household chores are also less likely to undertake joint discretionary activities (see discussion in Section 8.3.4).

8.3.5 Out-of-Home Maintenance Activity Participation Characteristics

The time invested in shopping by a person is found to negatively impact his/her out-of-home discretionary duration. Note from the discussion in the discrete component that men and women who undertake shopping are also more likely to undertake out-of-home discretionary activities. Thus, when participation in shopping positively influences out-of-home discretionary activity participation, the time invested in shopping constrains the duration of these discretionary activities. Finally, time invested in joint shopping is found to decrease both independent and joint discretionary activity duration (except in the case of female's in-home activities where there is no statistically significant effect).

8.3.6 Spouse's Activity Participation Characteristics

On examining the impact of the mandatory and maintenance activity participation choices of the spouses on independent discretionary activity durations, we find that duration invested by the wife in work and maintenance activities influences the husband's discretionary activity durations in many ways. Increasing time investment of the wife in work decreases the husband's discretionary activity duration. However, longer the wife spends in in-home maintenance, greater is the duration invested by the husband in out-of-home discretionary activities. Finally, husbands of wives, who spend longer time in shopping, spend lesser time in in-home discretionary activities. It is also interesting to note that there are no significant impacts of the husband's activity participation choices on the discretionary activity durations of the wife.

8.3.7 Spatial Variables

Working adults who have greater accessibility to retail and service opportunities from their work zone are found to spend more time in out-of-home discretionary activities. Perhaps, as a consequence of this greater accessibility, these adults are able to travel to these activity centers quickly and consequently have greater time available for activity participation. We also explored the impact of accessibility to opportunities from the home zone. However, these variables were not statistically significant.

8.3.8 Day-of-the-Week Variables

The male's discretionary activity duration is found to vary by the day of the week. Specifically, independent out-of-home discretionary activities undertaken on Mondays, and in-home discretionary activities undertaken on Thursdays are found to be of shorter durations.

8.3.9 Correlations Between the Discrete and Continuous Components

We found very strong *negative* correlations between the discrete and the continuous components of the choices in all the five cases (*i.e.,* "Male, IH", "Female, IH", "Male, OH", "Female, OH", and "Joint, OH"). Note that the error term ε_{iq} enters the utility expression in equation (16) with a negative sign. Therefore, a positive sign on the estimated correlation coefficient indicates negative correlations between the discrete and continuous components. In the case of "Male, OH" and "Joint, OH" the value of the correlation was fixed at 1 as we use an unconstrained optimization procedure (the MAXLIK library of functions) for the maximum likelihood estimation. The results suggest that unobserved factors that increase the propensity to undertake discretionary activities also decrease the activity duration. A plausible perspective on this result of negative error correlations is that, the individuals who desire to spend lesser time in discretionary activities are also the ones who are more likely to undertake discretionary activities, as shorter discretionary activities can be more easily accommodated within the overall weekday time constraints. Although, one could, at best, speculate on the behavioral interpretations of such correlations, it is still necessary to incorporate such effects in order to consistently estimate the impacts of the observed variables (Bhat, 1998).

Table 8.2 Model for Discretionary Activity Generation: Activity Duration

	Male, IH		Female, IH		Male, OH		Female, OH		Joint, OH	
	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.
Houshold Characteristics										
Income										
Low Income	0.094	2.592	-	-	-	-	-	-	-	-
Medium Income	0.066	2.189	-	-	-	-	-	-	-	-
Other										
Own HH	-	-	-	-	-	-	-	-	0.137	2.037
Number of Bicycles	-	-	-0.022	-2.296	-	-	-	-	0.064	2.898
Individual Characteristics										
Employment Status										
Employed Full-Time or Part-Time	-	-	-7.468	-3.406	-	-	-	-	-	-
Student Status										
Full-Time Student	-	-	-0.166	-1.708	-	-	-0.365	-3.262	-	-
Part-Time Student	-	-	-0.096	-1.697	-	-	-	-	-	-
Mandatory Activity Participation Characterisitics										
In-Home Work										
LN(IH Work Dur.)	-0.132	-14.903	-0.137	-11.862	-0.128	-7.075	-0.120	-6.830	-	-
Female's In-Home Work (for Joint, OH only)										
LN(IH Work Dur.)	-	-	-	-	-	-	-	-	-0.057	-2.568
Out-of-Home Work										
LN(OH Work Dur)	-0.138	-22.671	-0.134	-11.222	-0.329	-7.593	-0.341	-5.375	-	-
LN(OH Work Dur)*OH Work Dur. <= 4 Hours	1.016	5.984	0.848	4.454	-	-	0.837	3.297	-	-
LN(OH Work Dur)*OH Work Dur. <= 8 Hours	-0.959	-6.216	-0.841	-4.701	-	-	-0.523	-2.141	-	-
OH Work Dur. <= 4 Hours	-5.755	-5.871	-4.820	-4.375	-	-	-4.521	-3.070	-	-
OH Work Dur. <= 8 Hours	5.833	6.336	5.167	4.861	-	-	3.121	2.149	-	-
Commute Duration										
LN(Comm. Dur)*Comm. Dur. <= 30 mins.	-	-	0.564	2.767	-	-	-	-	-	-
LN(Comm. Dur)*Comm. Dur. <= 60 mins.	-	-	-0.508	-2.665	-	-	-	-	-	-
Comm. Dur. <= 30 mins.	-	-	-2.075	-2.762	-	-	-	-	-	-
Comm. Dur. <= 60 mins	-	-	1.856	2.569	-	-	-	-	-	-
Serve-Child										
Male Undertakes Serve-Child Activity	-	-	-	-	-0.305	-2.709	-	-	-	-
Female Undertakes Serve-Child Activity	-	-	-0.131	-2.926	-	-	-0.214	-3.507	0.274	1.734

Table 8.2 Model for Discretionary Activity Generation: Activity Duration (Continued)

	Male, IH		Female, IH		Male, OH		Female, OH		Joint, OH	
	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.
In-Home Maintenance Activity Participation Characterisitics										
<u>For all Persons</u>										
LN(IH Maint. Dur)	-	-	-1.091	-3.637	-1.699	-4.594	-1.055	-4.244	-	-
LN(IH Maint. Dur)*IH Maint. Dur. <= 2 hours	0.862	11.877	0.969	9.052	-	-	0.211	3.095	-	-
LN(IH Maint. Dur)*IH Maint. Dur. <= 6 hours	-0.928	-13.017	-0.688	-2.810	-	-	-	-	-	-
LN(IH Maint. Dur)*IH Maint. Dur. <= 10 hours	-	-	0.745	2.268	1.646	4.449	0.881	3.457	-	-
IH Maint. Dur. <= 2 hours	-4.392	-11.319	-5.064	-8.858	-	-	-0.939	-2.531	-	-
IH Maint. Dur. <= 6 hours	5.351	13.758	3.925	2.658	-	-	-	-	-	-
IH Maint. Dur. <= 10 hours			-4.868	-2.304	-10.487	-4.274	-5.611	-3.332	-	-
<u>For Non-Employed Persons</u>										
LN(IH Maint. Dur)	-	-	-1.109	-3.343	-	-	-	-	-	-
LN(IH Maint. Dur)*IH Maint. Dur. <= 2 hours	-	-	-0.699	-1.989	-	-	-	-	-	-
LN(IH Maint. Dur)*IH Maint. Dur. <= 6 hours	-	-	1.892	3.835	-	-	-	-	-	-
LN(IH Maint. Dur)*IH Maint. Dur. <= 10 hours	-	-	-0.084	-3.126	-	-	-	-	-	-
IH Maint. Dur. <= 2 hours	-	-	3.649	1.886	-	-	-	-	-	-
IH Maint. Dur. <= 6 hours	-	-	-11.265	-3.882	-	-	-	-	-	-
IH Maint. Dur. <= 10 hours	-	-	-	-	-	-	-	-	-	-
<u>For Joint, OH only</u>										
Male's IH Maint. Dur. <= 6 hours	-	-	-	-	-	-	-	-	0.372	4.758
Female's IH Maint. Dur. <= 10 hours	-	-	-	-	-	-	-	-	-0.346	-3.139
Out-of-Home Maintenance Activity Participation Characterisitics										
LN(Shopping Dur.)	-	-			-0.222	-6.166	-0.184	-8.715	-	-
LN(Joint Shopping Dur.)	-0.090	-2.919			-0.182	-3.172	-0.099	-1.566	-0.475	-7.695

Table 8.2 Model for Discretionary Activity Generation: Activity Duration (Continued)

	Male, IH		Female, IH		Male, OH		Female, OH		Joint, OH	
	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.	Beta	t. stat.
Spouse's Activity Participation Characteristics										
LN(IH Work Dur.)	-	-	-	-	-0.022	-1.485	-	-	-	-
LN(OH Work Dur)	-0.007	-1.521	-	-	-0.011	-1.374	-	-	-	-
LN(IH Maint. Dur)	-	-	-	-	0.044	2.977	-	-	-	-
LN(Shopping Dur.)	-0.017	-1.444	-	-			-	-	-	-
Spatial Variables										
Retail/Service Accessibility from Work Zone	-	-	-	-	0.651	4.489	0.580	2.728	-	-
Day-of the-Week Variables										
Monday	-	-	-	-	-0.171	-3.064	-	-	-	-
Thursday	-0.073	-2.207	-	-	-	-	-	-	-	-
Constant	5.704	107.848	20.224	10.174	16.530	6.712	12.312	7.425	6.109	48.172
S.D. of Error Term	0.815	94.597	0.904	70.659	1.594	63.841	1.414	64.896	1.331	40.616
Correlation between Discrete and Continuous Components	0.871	32.541	0.869	30.704	1.000	fixed	0.997	211.819	1.000	fixed
Log-likelihood at Convergence	-27957.20 (5381 cases)									
Log-likelihood for Constants only Model	-33728.59 (5381 cases)									
Adjusted Likelihood Ratio Index	0.166									

8.4 Error Covariance Among the Five Discrete-Continuous Components

The matrix of error covariances among the five discrete-continuous components of the model is presented in Table 8.3 (The values provided in parentheses are the *t* statistics). As the covariance matrix is symmetric, we present only the elements above the leading diagonal. The elements along the diagonal (*i.e.,* the variance terms) were normalized to one for model identification. Note that, as a consequence of this normalization of the variances to one, the covariances between error terms are also the correlations between the error terms.

Table 8.3 Matrix of Error Covariances Among the Discrete-Continuous Components

	Male, IH	Female, IH	Male, OH	Female, OH	Joint, OH
Male, IH	1	1 (Fixed)	-0.2492 (-8.565)	-0.2492 (-8.565)	-0.1871 (-3.903)
Female, IH		1	-0.2492 (-8.565)	-0.2492 (-8.565)	-0.1871 (-3.903)
Male, OH			1	1 (Fixed)	-0.0752 (-1.282)
Female, OH				1	-0.0752 (-1.282)
Joint, OH					1

The results indicate positive error correlations between the male and female in-home activity participation choices and similarly between the male and female out-of-home activity participation choices. This suggests that common unobserved factors favoring in-home activity participation of the husband are also found to favor in-home activity participation of the wife. Similarly, unobserved factors positively influencing independent out-of-home discretionary activity participation of the husband also positively impact the corresponding choice of the wife. Further, the two error correlations discussed above were fixed to one. This was required by empirical modeling considerations (these correlations were very strong) and because we used an unconstrained optimization technique for the maximum-likelihood estimation. The fixing of these error correlations to one imposes a particular structure to the covariance matrix. Specifically, the correlations between the following pairs of error terms become equal: Male-IH and Male-OH, Male-IH and Female-OH, Female-IH and Female-OH, and Female-IH and Male-OH (See the cells corresponding to the third and fourth columns for the first two rows in Table 8.3). This correlation was estimated to be negative suggesting intra-personal and inter-personal substitution effects between independent in-home and out-of-home activity participation choices of the household adults. Similarly, the correlation between the male's in-home activity choices and household's joint out-of-home activity choices, and the correlation between the female's in-home activity choices and household's joint out-of-home activity choices are equal and estimated to be negative. This indicates that unobserved factors that increase the propensity for independent in-home activity participation (such as life-style, habits, availability of in-home facilities, etc.) also decrease the propensity for joint activity out-of-home participation. Finally, the two remaining error correlation terms (*i.e.,* the correlation between the male's out-of-home activity choices and household's joint out-of-home activity choices, and the correlation between the female's out-of-home activity choices and household's joint out-of-home activity choices) are also equal. This correlation was estimated to be negative but not statistically very significant. As already indicated, the joint model with the error covariance structure as discussed above, is also found to fit the data better than five independent discrete continuous models.

8.5 Summary

This chapter presented the empirical models results for the discretionary activity generation. We find that the in-home and out-of-home work durations of a person very significantly influence his/her discretionary activity participation decisions. The in-home discretionary activity decisions are impacted by in-home maintenance time investments whereas shopping activity participation choices substantially influence the decisions relating to out-of-home discretionary activities. Finally, decisions relating to joint out-of-home discretionary activities are critically impacted by the number of children in the household and the need for one or both the adults to go to work.

Chapter 9 A Microsimulation Framework for Choice Predictions and a Demonstration of Model Application

9.1 Introduction

This chapter describes a microsimulation framework for using the model system developed in this dissertation to predict disaggregate, household-level activity-participation choices. Section 9.2 presents algorithms for each of the three components (*i.e.,* in-home maintenance activity generation, out-of-home maintenance activity generation, and discretionary activity generation) in the model system. Within an overall activity-based forecasting platform, these individual component algorithms can be applied sequentially to completely determine all the maintenance and discretionary activity participation choices (both in-home and out-of-home) of household adults. These choices, in turn, can form inputs to detailed activity-schedule forecasting models and thus, be used to determine the complete activity-travel patterns of each household adult. Section 9.3 presents a demonstration of model application for choice predictions and evaluation of the impacts of policy actions.

9.2 Disaggregate Prediction Algorithms for Individual Model Components

This section presents the simulation-based algorithms for using each of the three model components developed in this dissertation in predicting the corresponding activity-participation choices of the household adults. Section 9.2.1 presents the algorithm for predicting in-home maintenance activity participation choices using a seemingly unrelated regressions model. Next, in Section 9.2.2, the algorithm for predicting out-of-home maintenance activity participation choices using a joint mixed-logit hazard-duration model is discussed. Finally, Section 9.2.3 presents the algorithm for predicting discretionary activity participation choices using a multiple discrete-continuous model system.

9.2.1 Algorithm for Predicting In-Home Maintenance Activity Participation Choices

The algorithm for predicting the in-home maintenance activity participation choices of adults in household q, using a seemingly-unrelated regression model system, comprise the following steps (See section 4.2 for notation details):

(1) Compute the expected value of the logarithm of the male and female in-home maintenance durations using equation (1) in Chapter 4 as: $t_{Mq} = \beta_M X_{Mq}$ and $t_{Fq} = \beta_F X_{Fq}$.

(2) Draw random variates n_1 and n_2 from independent standard-normal distributions.

(3) Compute $\left[\varepsilon_{Mq}, \varepsilon_{Fq}\right] = \left[n_1, n_2\right]\Sigma^{1/2}$, where, $\Sigma^{1/2} = \begin{bmatrix} \sigma_M & \rho\sigma_F \\ 0 & \sigma_F\sqrt{1-\rho^2} \end{bmatrix}$ is the Cholesky decomposition of the covariance matrix, Σ, of the error terms ε_{Mq} and ε_{Fq}.

(4) Determine the in-home maintenance durations of the male and female as $\exp(t_{Mq} + \varepsilon_{Mq})$ and $\exp(t_{Fq} + \varepsilon_{Fq})$ respectively.

(5) Apply consistency checks as appropriate to ensure that the durations are neither too small nor too large. Note that Step 4 will always result in the prediction of positive durations.

9.2.2 Algorithm for Predicting Out-of-Home Maintenance Activity Participation Choices

Predicting choices using a joint mixed-logit hazard-duration model system involves the determination of choice probabilities that do not have a closed form analytical expression. Rather, the computations involve the evaluation of a multidimensional integral over the elements in the vector of error terms ω (See section 4.3 for notation details; we suppress the index for households, *i.e.,* q, from hereon for ease in presentation). This integration is performed using a simulation approach. Specifically, the conditional probabilities are computed for different realizations of ω drawn from its multivariate normal distribution function (with zero means, and covariance, Σ) and averaged to obtain an approximation of the unconditional choice probabilities.

The algorithm for predicting the out-of-home maintenance activity participation choices of adults in a household, using a joint mixed-logit hazard-duration model system, comprises the following steps:

(1) Compute the deterministic components of each of the four discrete choice alternatives using equation (4) as (with the index for households suppressed): $U_i = \beta_i Z_i$ for *i* = N, M, F, and J.

(2) Compute the deterministic components of the integrated hazards for each of the three duration choices corresponding to discrete alternatives, *i* = M, F, and J using equation (8) as: $s_i^* = \gamma_i X_i$.

(3) The steps (4), (5), and (6) are repeated for r = 1 to R (R is a very large number, say 10,000). Each iteration of this loop results in the computation of the conditional choice probabilities corresponding to the r^{th} draw.

(4) Draw random variates n_N^r, n_M^r, n_F^r, and n_J^r from independent standard-normal distributions.

(5) Compute $\omega^r = \left[\omega_N^r, \omega_M^r, \omega_F^r, \omega_J^r\right] = \left[n_N^r, n_M^r, n_F^r, n_J^r\right]\Sigma^{1/2}$, where, $\Sigma^{1/2}$ is the Cholesky decomposition of the estimated covariance matrix, Σ, of the vector of error terms *ω*.

(6) Compute P_N^r, the conditional probability (from the r^{th} draw) that the household does not shop using equation (13). Let P_{M,k_M}^r be the conditional probability (from the r^{th} draw) that the household allocates the shopping responsibility to the male with a discrete duration of k_M (for k_M =1,2,3… K_M). Similarly, let P_{F,k_F}^r and P_{J,k_J}^r represent the corresponding conditional probabilities that the shopping is allocated to the female and jointly to both, and with discrete durations of k_F and k_J respectively (for k_F =1,2,3… K_F and k_J =1,2,3… K_J). Compute these

conditional probabilities, (*i.e.,* P^r_{M,k_M} , P^r_{F,k_F} , and P^r_{J,k_J}) using equation (12).

(7) Compute the unconditional choice probabilities by averaging the corresponding conditional probabilities determined for the R draws. Let the unconditional probability that household does not shop be P_N . Let the unconditional probability that household allocates the shopping responsibility to the male with a discrete duration of k_M (for k_M =1,2,3… K_M) be P_{M,k_M} . Similarly, let P_{F,k_F} and P_{J,k_J} represent the corresponding unconditional probabilities that the shopping is allocated to the female and jointly to both, and with discrete durations of k_F and k_J respectively (for k_F =1,2,3… K_F and k_J =1,2,3… K_J).

(8) Draw a random variate u from a uniform [0,1] distribution.

(9) If $u \le P_N$ then, assign no shopping as the chosen alternative. If $P_N < u \le \left(P_N + P_{M,1}\right)$, then, assign male shopping with duration equal to the first discrete period (*i.e,* $T \in [0, T^1_M]$) as the chosen alternative. If $\left(P_N + P_{M,1}\right) < u \le \left(P_N + P_{M,1} + P_{M,2}\right)$then, assign male shopping with duration equal to the second discrete period (*i.e,* $T \in [T^1_M, T^2_M]$) as the chosen alternative. Similarly, by extending the above assignment rule, the choice of the household can be determined as one of the alternatives.

(10) Step (9) determines only the discrete period (say $T \in [T^{k-1}, T^k]$) for shopping duration. To determine the duration on a continuous scale, draw a random variate v from a uniform [0,1] distribution. The continuous shopping duration is computed as $T^{k-1} + (T^k - T^{k-1})v$ (Note that this assumes that the durations within the discrete period are all equally likely). Further, the upper bound of the last discrete time period is generally infinity. Hence, if the last discrete time period

is chosen, a reasonable upper bound should be defined to determine the duration on a continuous scale.

9.2.3 Algorithm for Predicting Discretionary Activity Participation Choices

Predicting choices using a multiple discrete-continuous model system also require the computation of choice probabilities that involves evaluation of a multidimensional integral over the elements in the vector of error terms ω (See section 4.4 for notation details; again, we suppress the index for households, *i.e., q*). This integration is performed using a simulation approach. Specifically, the conditional probabilities are computed for different realizations of ω drawn from its multivariate normal distribution function (with zero means, and covariance, Σ) and averaged to obtain an approximation of the unconditional choice probabilities.

The algorithm for predicting the discretionary activity participation choices of adults in household, using a multiple discrete-continuous model system, comprise the following steps:

(1) Compute the deterministic utilities of undertaking each of the five activity types (*i.e.,* male in-home, female in-home, male out-of-home, female out-of-home, and joint out-of-home) using equation (16) as: $U_i = \beta_i Z_i$ for i = MIH, FIH, MOH, FOH, and JOH.

(2) Repeat steps (3), (4), and (5) are repeated for r = 1 to R (R is a very large number, say 10,000). Each iteration of this loop results in the computation of the conditional choice probabilities corresponding to the r^{th} draw.

(3) Draw random variates $n^r_{MIH}, n^r_{FIH}, n^r_{MOH}, n^r_{FOH}$, and n^r_{JOH} from independent standard-normal distributions.

(4) Compute:

$$\omega^r = \left[\omega^r_{MIH}, \omega^r_{FIH}, \omega^r_{MOH}, \omega^r_{FOH}, \omega^r_{JOH}\right] = \left[n^r_{MIH}, n^r_{FIH}, n^r_{MOH}, n^r_{FOH}, n^r_{JOH}\right]\Sigma^{1/2}$$

, where, $\Sigma^{1/2}$ is the Cholesky decomposition of the estimated covariance matrix, Σ, of the vector of error terms ω.

(5) Compute P_i^r, the conditional probability (from the r^{th} draw) of undertaking activity of type *i* (for *i* = MIH, FIH, MOH, FOH, and JOH), using equation (17).

(6) Compute the unconditional choice probabilities, P_i of undertaking activity of type *i* (for *i* = MIH, FIH, MOH, FOH, and JOH) by averaging the corresponding conditional probabilities determined for the R draws.

(7) Draw random variates $u_{MIH}, u_{FIH}, u_{MOH}, u_{FIH}$, and u_{JOH} from independent uniform [0,1] distributions.

(8) If $u_i \leq P_i$, the household is assigned to undertake activity of type *i* (for each of *i* = MIH, FIH, MOH, FOH, and JOH), else, the household is assigned to not undertake the activity of type *i*.

(9) Let *j* represent the set of activity types the household has been determined to undertake from step (8). Therefore, $j \subset [MIH, FIH, MOH, FOH, JOH]$. The continuous activity durations are determined only for these activity types. The procedure presented here uses Lee's selectivity correction (the term $\rho_j \sigma_{\eta j} \lambda_j$ in Step 11 represents this correction) for sample selection models (Lee, 1979). The determination of the variance of the error term (s_j) in the regression model for activity duration, after accounting for this selectivity correction, uses the properties of the truncated bivariate normal distributions (See, for example, pp. 927 in Greene, 2000). Compute:

$$\alpha_j = \Phi^{-1}[P_j]$$

$$\lambda_j = \frac{-\phi(\alpha_j)}{P_j}$$

$$\delta_j = \lambda_j(\lambda_j - \alpha_j)$$

$$s_j^2 = \sigma_{\eta j}^2(1 - \rho_j \delta_j^2)$$

(10) Draw random variates n_j from independent standard-normal distributions.

(11) Compute the activity duration for type *j* (on a continuous scale) as: $\exp\left(\theta_j X_j + \rho_j \sigma_{\eta j} \lambda_j + s_j n_j\right)$.

(12) Apply consistency checks as appropriate to ensure that the durations are neither too small nor too large. Note that Step 11 will always result in the prediction of positive durations.

9.3 Demonstration of Model Application

The focus of this section is to present a demonstration of the application of the developed model system in predicting the activity-participation choices of adults and in studying the impact of transportation policy actions on these choices. Further, the intent here is also to highlight the advantages of activity-based models that accommodate household interactions over individual-level models. Specifically, activity-based models that accommodate household interactions offer three main advantages over individual-level models in the evaluation of the impact of the policy actions. First, models accommodating household interactions capture the changes in the activity participation behavior of the spouse who is not directly impacted by the policy action. Second, such models accommodate the impact of the activity participation choices of the spouse in the personal response of an individual to a policy action. Third, the models accommodating household interactions can also be used to predict policy impacts on the activities undertaken jointly by the household adults. Individual-level models, however, do not distinguish between independent and joint activities.

The demonstration study presented here examines disaggregate (*i.e.,* household-level) impacts of three different travel-demand management policy actions that alter the work duration and commute characteristics in different ways. These policy actions are: (1) Early release from work, (2) Compressed workweek, and (3) Home-based telecommuting. All these three policy actions have been identified as important transportation control measures for congestion management and air quality improvement (see, for example, Stopher, 1993).

Further, we also compare the impact of these three policy actions on the following three types of households: (1) Single worker household in which is the female is not employed, (2) Dual-worker household in which the female is a part-time employee, and (3) Dual worker household in which the female is a full-time employee. In all the three types of households, the male is assumed to be a full-time employee working for 8.5 hours during the day with the work ending between 4 and 6 PM. The expected two-way commute duration for the male is taken as 1 hour. Both the male and female heads of the household are middle-aged, non-students, and have access to a personal vehicle. All the three types of the households are assumed to be of Caucasian ethnicity, living in own homes, and with access to the Internet from home. Finally, there are no children present in the households examined here.

As already indicated, we examine the impact of three different policy actions on the activity-participation choices of adults in three types of households. For the third type of household, (*i.e.,* dual worker household in which both male and female are full time workers), we examine the impacts when each of the male and female heads of the household are directly impacted by the policy actions. Hence, for each policy action, four scenarios are examined in all (one each for the first two types of households and two for the third type of household). For each of the four scenarios, 1000 simulation runs each are made for the base-case and for the policy case. The algorithms presented in Section 9.2 were coded in the matrix programming language, GAUSS, and used for the analyses.

9.3.1 Impacts of Early Release From Work

The first travel demand management policy action examined is early release from work. The intent of this employer-based demand-management policy is to spread the evening peak period traffic over a longer period of time and thereby reduce the traffic congestion, which would otherwise occur during a shorter time period in the evening. In the base case, the full-time worker in the household is assumed to work for 8.5 hours with work ending between 4 and 6 PM, which is often the "evening peak" period. The expected two-way commute duration is assumed to be 1 hour. In the policy case scenario, this person is assumed to be released from work 2.5 hours before the regular scheduled work end time. Hence, the work duration is now 6 hours and the work ends before 4 PM. Also, the expected two-way commute duration in the policy scenario is taken as 50 minutes (as the person is now expected to make the return-home trip during the off-peak period).

The impact of early release from work on in-home maintenance durations is presented in Table 9.1. The table presents the average in-home maintenance durations (averaged over the 1000 simulations) for the base case and the policy case and also the percentage difference between these mean durations. The results indicate that early release from work increases the in-home time invested by the worker in household chores, presumably due to higher time availability in the policy scenario. In the case of men, the percentage increase in in-home maintenance duration is greater when the wife is employed compared to when the wife is not employed. In dual worker households, the percentage increase in the in-home chores duration of the male when released early from work is greater than the percentage increase in the in-home chores duration of the female when she is released early from work. Finally, the table also indicates a small decrease in the in-home maintenance duration of the female when the male is released early from work.

Table 9.1 Impact of Early Release from Work on In-Home Maintenance Durations

		Male	Female
Female is not employed	Base Case	247.74	465.94
	Policy Case[1]	253.49	463.08
	% Diff.	2.32	-0.61
Female is part-time employed	Base Case	251.82	350.00
	Policy Case[1]	278.34	347.40
	% Diff.	10.53	-0.74
Female is full-time employed	Base Case	251.82	288.56
	Policy Case[1]	278.34	286.10
	% Diff.	10.53	-0.86
Female is full-time employed	Base Case	251.82	288.56
	Policy Case[2]	251.82	292.66
	% Diff.	0.00	1.42

[1] Male is released early from work
[2] Female is released early from work

The impact of the policy action on out-of-home maintenance activity (grocery shopping) participation choices is presented in Table 9.2. For the discrete component of the choice (*i.e.,* decision to shop and task allocation), the table presents the number of times each of the alternatives was predicted to be chosen over the 1000 simulations (for each of the base case and the policy case). For example, the entry 778 under "No Shop" for the base case for the first scenario indicates that of the 1000 simulation runs for this base case scenario, the household was predicted to not undertake shopping in 778 of the runs. Note that the numbers sum to 1000 across the four discrete choice alternatives. In addition to the number of the times the different alternatives were chosen, the table also presents the percentage difference between the policy case and the base case predictions for each alternative. For the continuous component of the choice, (*i.e.,* activity duration), the table presents the average shopping durations (averaged over the households predicted to choose the corresponding discrete choice alternative) for the base case and the policy case and also the percentage difference between these mean durations. The results indicate that a worker when released early from work is more likely to shop compared to a person who works for the normal duration. This increase in the likelihood to undertake shopping is greater for the females compared to the males. Further, we also observe that task re-allocations are less likely to occur in all the four scenarios examined here. In summary, early release from work is most likely to lead to additional shopping trips undertaken taken by the person released early from work. Finally, the duration invested by this person (*i.e.,* the person released early from work) in shopping is also greater.

Table 9.2 Impact of Early Release from Work on Out-of-Home Maintenance Activity Participation

		Decision to Shop and Task Allocation				Shopping Duration		
		No Shop	Male Shop	Female Shop	Joint Shop	Male Shop	Female Shop	Joint Shop
Female is not employed	Base Case	778	25	182	15	15.12	37.53	55.10
	Policy Case[1]	770	34	181	15	23.45	37.06	55.10
	% Diff.	-1.03	36.00	-0.55	0.00	55.08	-1.26	0.00
Female is part-time employed	Base Case	805	40	139	16	16.92	37.12	35.92
	Policy Case[1]	797	52	136	15	29.83	37.38	37.81
	% Diff.	-0.99	30.00	-2.16	-6.25	76.29	0.69	5.25
Female is full-time employed	Base Case	880	35	68	17	14.70	22.35	36.20
	Policy Case[1]	865	50	68	17	21.92	21.33	36.20
	% Diff.	-1.70	42.86	0.00	0.00	49.11	-4.56	0.00
Female is full-time employed	Base Case	880	35	68	17	14.70	22.35	36.20
	Policy Case[2]	844	34	105	17	14.21	33.87	35.06
	% Diff.	-4.09	-2.86	54.41	0.00	-3.33	51.53	-3.14

[1] Male is released early from work

[2] Female is released early from work

The impact of the policy action on discretionary activity participation choices is presented in Tables 9.3 and 9.4. Table 9.3 presents the impact on the decision to undertake discretionary activities. This table presents the number of times each of the five discretionary activity types (*i.e.,* male in-home, female, in-home, male out-of-home, female, out-of-home, and joint out-of-home) was predicted to be undertaken over the 1000 simulations (for each of the base case and the policy case). For example, the entry 541 under "Male, IH" for the base case for the first scenario indicates that of the 1000 simulation runs for this base case scenario, the male was predicted to undertake in-home discretionary activities in 541 of the runs (alternatively, the male was predicted to not undertake in-home discretionary activities in the remaining 459 runs). In addition to the number of the times each activity type were chosen, the table also presents the percentage difference between the policy case and the base case predictions for each activity type. The table indicates that a person released early from work results is more likely to undertake both in-home and out-of-home independent discretionary activities. Further, the percentage increase in the likelihood of undertaking out-of-home discretionary activities is greater than the increase in the probability of undertaking in-home discretionary activities suggesting that early release from work is likely to result in additional trips for discretionary purposes. The spouse of the person released early from work is also found to be more likely to undertake out-of-home discretionary activities in the policy scenario. Thus, early release from work is not only likely to result in additional trips for the person directly impacted by the policy, but also lead to increased travel of his/her spouse. Finally, the propensity to undertake joint activities is found to increase when the male is released early from work, with the extent of this increase varying depending on the work characteristics of the wife.

Table 9.3 Impact of Early Release from Work on Discretionary Activity Participation

		Male, IH	Female, IH	Male, OH	Female, OH	Joint, OH
Female is not employed	Base Case	541	624	319	612	165
	Policy Case[1]	637	627	528	638	252
	% Diff.	17.74	0.48	65.52	4.25	52.73
Female is part-time employed	Base Case	485	656	356	571	149
	Policy Case[1]	566	656	561	601	211
	% Diff.	16.70	0.00	57.58	5.25	41.61
Female is full-time employed	Base Case	490	454	322	363	104
	Policy Case[1]	570	450	527	389	165
	% Diff.	16.33	-0.88	63.66	7.16	58.65
Female is full-time employed	Base Case	490	454	322	363	104
	Policy Case[2]	489	529	357	562	104
	% Diff.	-0.20	16.52	10.87	54.82	0.00

[1] Male is released early from work
[2] Female is released early from work

Table 9.4 presents the impact on the discretionary activity durations. This table presents the average discretionary activity durations (averaged over the households predicted to choose the corresponding discretionary activity type) for the base case and the policy case and also the percentage difference between these mean durations. The table indicates that a person released early from work is likely to spend more time in both in-home and out-of-home discretionary activities, presumably due to increased time availability. In addition, the spouse of the person impacted by the policy is also likely to spend more time in out-of-home discretionary activities. Finally, joint activities undertaken when the male is released early from work, is found to be of greater duration compared to the duration of the joint discretionary activities undertaken when the male works for the regular hours.

Table 9.4 Impact of Early Release from Work on Discretionary Activity Durations

		Male, IH	Female, IH	Male, OH	Female, OH	Joint, OH
Female is not employed	Base Case	274.67	383.23	49.61	144.28	95.39
	Policy Case[1]	337.45	385.07	93.52	149.09	116.04
	% Diff.	22.86	0.48	88.53	3.33	21.64
Female is part-time employed	Base Case	256.07	328.08	50.60	104.81	82.02
	Policy Case[1]	305.57	329.53	94.48	110.19	108.36
	% Diff.	19.33	0.44	86.72	5.14	32.11
Female is full-time employed	Base Case	256.86	193.02	43.92	43.41	67.14
	Policy Case[1]	305.96	192.47	86.96	46.80	84.68
	% Diff.	19.11	-0.28	98.01	7.80	26.12
Female is full-time employed	Base Case	256.86	193.02	43.92	43.41	67.14
	Policy Case[2]	255.93	275.49	50.60	76.24	67.14
	% Diff.	-0.36	42.73	15.22	75.61	0.00

[1] Male is released early from work

[2] Female is released early from work

9.3.2 Impacts of Compressed Workweek

The second policy action examined here is a compressed workweek. The intent of this policy is to replace the typical five-day workweek by a four-day workweek by requiring the employees to work for longer durations during the four working days. This action therefore eliminates the need to undertake commute travel on one of the days. The focus of the analysis is on the activity-participation choices on this day, *i.e.,* the day on which the full-time worker does not have to go to work. Hence, in the policy case scenarios, the out-of-home work duration and the commute duration are set to zero for the person impacted by the policy. In addition, the variable “accessibility to retail and service employment from the work zone” is also reset to zero.

The impact of a compressed workweek policy on in-home maintenance durations is presented in Table 9.5. In the case of a single worker household, the male is found to spend increased time in household chores whereas the in-home maintenance time investment of the female decreases on the day in which the worker does not have to go to work. In dual-worker households, the male is found not to spend any more time on the day in which he does not go to work compared to the day in which he spends more than 8 hours at work. However, the time invested by his spouse is lesser on the extended weekend day compared to the normal workday. The impacts are different when the schedule of the wife is a compressed workweek. Specifically, the female is found to spend more time in household chores on the day in which she does not have to go to work when compared to the day in which she spends more than 8 hours at work. There is however, no change in the in-home duration of her husband as a consequence of this policy.

Table 9.5 Impact of Compressed Workweek on In-Home Maintenance Durations

		Male	Female
Female is not employed	Base Case	247.74	465.94
	Policy Case[1]	310.07	414.90
	% Diff.	25.16	-10.95
Female is part-time employed	Base Case	251.82	350.00
	Policy Case[1]	251.82	304.88
	% Diff.	0.00	-12.89
Female is full-time employed	Base Case	251.82	288.56
	Policy Case[1]	251.82	246.50
	% Diff.	0.00	-14.58
Female is full-time employed	Base Case	251.82	288.56
	Policy Case[2]	251.82	363.36
	% Diff.	0.00	25.92

[1] Male does not have to go to work
[2] Female does not have to go to work

The impact of the policy action on out-of-home maintenance activity (grocery shopping) participation choices is presented in Table 9.6. The results indicate that a worker who does not go to work is more likely to shop compared to a person who works for the normal duration. Again, as in the case of the policy of early release in work, this increase in the likelihood to undertake shopping is greater for the females compared to the males. We also find that the shopping task is likely to be re-allocated to the worker who does not have to go to work from his/her spouse. Further, the likelihood of reallocation from the male to his wife, who does not have to go to work, is significantly greater than the likelihood of reallocation of shopping from the female to the male, who does not have to go to work. In summary, compressed workweek policies is likely to both generate additional shopping trips and also result in re-allocation of shopping responsibilities on the day in which the worker does not have to work. Finally, shopping durations on a non-working day are also greater than the shopping durations on a working day.

Table 9.6 Impact of Compressed Workweek on Out-of-Home Maintenance Activity Participation

		Decision to Shop and Task Allocation				Shopping Duration		
		No Shop	Male Shop	Female Shop	Joint Shop	Male Shop	Female Shop	Joint Shop
Female is not employed	Base Case	778	25	182	15	15.12	37.53	55.10
	Policy Case[1]	763	48	174	15	21.73	37.92	53.22
	% Diff.	-1.93	92.00	-4.40	0.00	43.70	1.03	-3.42
Female is part-time employed	Base Case	805	40	139	16	16.92	37.12	35.92
	Policy Case[1]	794	57	134	15	30.00	37.10	37.81
	% Diff.	-1.37	42.50	-3.60	-6.25	77.30	-0.07	5.25
Female is full-time employed	Base Case	880	35	68	17	14.70	22.35	36.20
	Policy Case[1]	855	62	66	17	23.84	20.82	36.20
	% Diff.	-2.84	77.14	-2.94	0.00	62.22	-6.87	0.00
Female is full-time employed	Base Case	880	35	68	17	14.70	22.35	36.20
	Policy Case[2]	782	24	179	15	14.79	38.55	37.81
	% Diff.	-11.14	-31.43	163.24	-11.76	0.63	72.46	4.44

[1] Male does not go to work
[2] Female does not go to work

The impact of the policy action on discretionary activity participation choices is presented in Tables 9.7 and 9.8. Table 9.7 presents the impact on the decision to undertake discretionary activities. The table clearly indicates that a worker who does to have to go to work is more likely to undertake both in-home and out-of-home independent discretionary activities. Also, the increase in the likelihood of undertaking in-home discretionary activities is greater than the corresponding increase observed in the case of early-release from work. When the husband does not have to go to work, the wife is found to be more likely to undertake in-home discretionary activities. This is perhaps because the decreased in-home maintenance duration of the wife in the policy scenario (see discussion on impacts on maintenance activities) facilitates her in-home discretionary activity participation. Further, unlike in the case of early release from work, when the spouse was found to be more likely to undertake out-of-home discretionary activities, the increase in the likelihood of out-of-home discretionary activity participation of the spouse is not significant in the case of a compressed workweek policy. Finally, the propensity to undertake joint activities is found to increase when a worker in the household does not go to work. The percentage increase in the likelihood of joint activity participation is greater when the male does not work compared to the scenario in which the female does not have to go to work.

Table 9.7 Impact of Compressed Workweek on Discretionary Activity Participation

		Male, IH	Female, IH	Male, OH	Female, OH	Joint, OH
Female is not employed	Base Case	541	624	319	612	165
	Policy Case[1]	678	640	538	613	325
	% Diff.	25.32	2.56	68.65	0.16	96.97
Female is part-time employed	Base Case	485	656	356	571	149
	Policy Case[1]	690	693	567	574	284
	% Diff.	42.27	5.64	59.27	0.53	90.60
Female is full-time employed	Base Case	490	454	322	363	104
	Policy Case[1]	700	503	538	366	219
	% Diff.	42.86	10.79	67.08	0.83	110.58
Female is full-time employed	Base Case	490	454	322	363	104
	Policy Case[2]	484	586	317	616	172
	% Diff.	-1.22	29.07	-1.55	69.70	65.38

[1] Male does not have to work
[2] Female does not have to work

Table 9.8 presents the impact on the activity duration. The table indicates that a person who does not have to go to work is likely to spend more time in both in-home and out-of-home discretionary activities, presumably due to increased time availability. The spouse of the person impacted by the policy is also likely to spend more time in in-home and out-of-home independent discretionary activities. Finally, joint activities undertaken when one of the spouses does not go to work, are found to be of greater duration than the duration of joint discretionary activities undertaken when both work for the regular hours on all five days of the week.

Table 9.8 Impact of Compressed Workweek on Discretionary Activity Durations

		Male, IH	Female, IH	Male, OH	Female, OH	Joint, OH
Female is not employed	Base Case	274.67	383.23	49.61	144.28	95.39
	Policy Case[1]	467.66	404.47	155.18	148.83	132.39
	% Diff.	70.26	5.54	212.82	3.15	38.78
Female is part-time employed	Base Case	256.07	328.08	50.60	104.81	82.02
	Policy Case[1]	463.93	351.13	161.71	107.84	122.57
	% Diff.	81.17	7.03	219.59	2.89	49.43
Female is full-time employed	Base Case	256.86	193.02	43.92	43.41	67.14
	Policy Case[1]	460.85	206.17	152.15	45.00	104.55
	% Diff.	79.41	6.81	246.45	3.66	55.71
Female is full-time employed	Base Case	256.86	193.02	43.92	43.41	67.14
	Policy Case[2]	263.46	412.29	49.04	155.08	93.57
	% Diff.	2.57	113.60	11.67	257.20	39.36

[1] Male does not have to work
[2] Female does not have to work

9.3.3 Impacts of Home-Based Telecommuting

The final policy action studied is that of home-based telecommuting. Telecommuting from home, as opposed to the conventional travel to work, eliminates the need for undertaking commute travel and therefore may be expected to reduce the peak period traffic levels. In our analysis, we assume that this policy requires the person to work in-home for 8.5 hours instead of working for the same duration at an out-of-home location. Hence, this policy action is “implemented” within our empirical framework by setting the out-of-home work duration and the commute duration as zero, and setting the in-home work duration as 510 minutes. In addition, the variable “accessibility to retail and service employment from the work zone” is also reset to zero, as the person is no longer traveling out-of-home to work.

The impact of home-based telecommuting on in-home maintenance durations is presented in Table 9.10. We observe that persons working from home spend significantly lesser time in household chores when compared to persons who work at an out-of-home location (the in-home and out-of-home work durations being equal). Also, the wife of a person who works in-home is found to spend lesser time in household chores compared to the wife of a person who spends an equal amount of time in work at an out of home location.

Table 9.9 Impact of Home-based Telecommuting on In-Home Maintenance Durations

		Male	Female
Female is not employed	Base Case	247.74	465.94
	Policy Case[1]	148.13	414.90
	% Diff.	-40.21	-10.95
Female is part-time employed	Base Case	251.82	350.00
	Policy Case[1]	159.24	304.88
	% Diff.	-36.77	-12.89
Female is full-time employed	Base Case	251.82	288.56
	Policy Case[1]	159.24	246.50
	% Diff.	-36.77	-14.58
Female is full-time employed	Base Case	251.82	288.56
	Policy Case[2]	251.83	178.27
	% Diff.	0.00	-38.22

[1] Male telecommutes from home
[2] Female telecommutes from home

The impact of the policy action on out-of-home maintenance activity (grocery shopping) participation choices is presented in Table 9.10. The results indicate increased likelihood of the generation of shopping trips to be undertaken by the person telecommuting as well as re-allocation of shopping tasks to the person who is now working from home. The reader will note that the impacts are very similar to those discussed in the context of the compressed workweek policy (See Table 9.6 and associated discussions). This is because, the in-home work characteristics were not found to be statistically significant descriptors of shopping related choices in our empirical model specifications (See Chapter 7). Finally, it is also interesting to note that none of the three policy actions examined here significantly impact choices relating to joint grocery shopping. This is intuitive because joint pursuit of grocery shopping can be expected to be motivated by resource constraints (*i.e.,* non availability of multiple vehicles) rather than companionship desires.

Table 9.10 Impact of Home-based Telecommuting on Out-of-Home Maintenance Activity Participation

		Decision to Shop and Task Allocation				Shopping Duration		
		No Shop	Male Shop	Female Shop	Joint Shop	Male Shop	Female Shop	Joint Shop
Female is not employed	Base Case	778	25	182	15	15.12	37.53	55.10
	Policy Case[1]	765	46	174	15	21.91	38.01	53.22
	% Diff.	-1.67	84.00	-4.40	0.00	44.87	1.27	-3.42
Female is part-time employed	Base Case	805	40	139	16	16.92	37.12	35.92
	Policy Case[1]	795	56	134	15	30.45	37.17	37.81
	% Diff.	-1.24	40.00	-3.60	-6.25	79.95	0.13	5.25
Female is full-time employed	Base Case	880	35	68	17	14.70	22.35	36.20
	Policy Case[1]	856	61	66	17	23.14	20.82	36.20
	% Diff.	-2.73	74.29	-2.94	0.00	57.46	-6.87	0.00
Female is full-time employed	Base Case	880	35	68	17	14.70	22.35	36.20
	Policy Case[2]	794	26	165	15	13.17	37.28	37.81
	% Diff.	-9.77	-25.71	142.65	-11.76	-10.40	66.81	4.44

[1] Male telecommutes from home
[2] Female telecommutes from home

The impact of the policy action on discretionary activity participation choices is presented in Tables 9.11 and 9.12. Table 9.11 presents the impact on the decision to undertake discretionary activities. This table indicates that a worker who telecommutes from home is more likely to undertake both independent in-home and out-of-home discretionary activities. Also, the increase in the likelihood of undertaking in-home discretionary activities is greater than the corresponding increase observed in the case of compressed workweek. When one of the adults telecommutes from home (and spends more than 8 hours in in-home work), the spouse is also found to be more likely to undertake in-home discretionary activities. Again, this increase in the likelihood of in-home discretionary activity participation of the spouse is greater than the corresponding increase observed in the case of the compressed workweek policy. Finally, the propensity to undertake joint activities is found to increase when a worker telecommutes from home.

Table 9.11 Impact of Home-Based Telecommuting on Discretionary Activity Participation

		Male, IH	Female, IH	Male, OH	Female, OH	Joint, OH
Female is not employed	Base Case	541	624	319	612	165
	Policy Case[1]	830	661	547	613	325
	% Diff.	53.42	5.93	71.47	0.16	96.97
Female is part-time employed	Base Case	485	656	356	571	149
	Policy Case[1]	794	705	574	574	284
	% Diff.	63.71	7.47	61.24	0.53	90.60
Female is full-time employed	Base Case	490	454	322	363	104
	Policy Case[1]	798	514	545	366	219
	% Diff.	62.86	13.22	69.25	0.83	110.58
Female is full-time employed	Base Case	490	454	322	363	104
	Policy Case[2]	500	780	317	625	190
	% Diff.	2.04	71.81	-1.55	72.18	82.69

[1] Male telecommutes from home
[2] Female telecommutes from home

Table 9.12 presents the impact on the activity duration. We find that a person who telecommutes is likely to spend more time in both in-home and out-of-home discretionary activities. The average discretionary activity duration (both in-home and out-of-home) of the person telecommuting is, however, less than the corresponding average durations of persons not going to work as a result of a compressed work week policy, presumably because of the greater time constraints in the former policy scenario. The spouse of the person impacted by the policy is also likely to spend more time in in-home and out-of-home independent discretionary activities. Finally, joint activities undertaken when the male telecommutes, are found to be, on average, of greater duration compared to the duration of joint discretionary activities undertaken when the male works out-of-home for the regular hours. However, the duration of joint activities undertaken when the wife telecommutes is found to be comparable to the duration when the female works out-of-home for the regular hours.

Table 9.12 Impact of Home-Based Telecommuting on Discretionary Activity Durations

		Male, IH	Female, IH	Male, OH	Female, OH	Joint, OH
Female is not employed	Base Case	274.67	383.23	49.61	144.28	95.39
	Policy Case[1]	323.88	404.59	99.33	148.82	138.52
	% Diff.	17.91	5.57	100.23	3.15	45.21
Female is part-time employed	Base Case	256.07	328.08	50.60	104.81	82.02
	Policy Case[1]	303.96	350.97	99.13	107.90	127.03
	% Diff.	18.70	6.98	95.91	2.95	54.87
Female is full-time employed	Base Case	256.86	193.02	43.92	43.41	67.14
	Policy Case[1]	303.34	207.93	91.23	45.00	108.53
	% Diff.	18.09	7.73	107.74	3.66	61.63
Female is full-time employed	Base Case	256.86	193.02	43.92	43.41	67.14
	Policy Case[2]	266.84	295.19	40.96	100.05	66.21
	% Diff.	3.88	52.93	-6.72	130.45	-1.39

[1] Male telecommutes from home
[2] Female telecommutes from home

Chapter 10 Conclusion

10.1 Introduction

The recognition of household interactions in activity-travel modeling is very important for realistic analyses of the behavioral responses of households to changes in land-use, transportation system, and individual and household socio-economic characteristics. In contrast to this importance of accommodating inter-personal dependencies in activity modeling, much of the research efforts have focused on modeling individuals' activity patterns independent of the activity-travel choices of other household members.

This dissertation seeks to contribute to the area of activity-based travel-demand modeling by examining the impact of household interactions in shaping the daily activity participation choices of individuals. Specifically, we focus on modeling weekday in-home and out-of-home maintenance and discretionary activity participation choices of adults in active, nuclear family, households. A comprehensive analysis framework was developed and data from the 2000 Bay Area Travel Survey were used in model estimations.

The rest of this chapter presents an overview of the methodological contributions of this study, summarizes the important empirical results, and finally, identifies directions for further research.

10.2 Methodological Contributions

This section discusses the methodological contributions of this dissertation. These are discussed under three main headings: (1) the overall analysis framework, (2) flexible discrete-continuous models, and (3) algorithms for disaggregate predictions.

10.2.1 The Overall Analysis Framework

This dissertation presents an overall analysis framework for modeling the daily in-home and out-of-home activity participation choices of adults in active, nuclear family, households, as an outcome of individual and household needs, desires, opportunities, and spatio-temporal and resource constraints. This overall framework explicitly captures several kinds of interactions between the household heads. These include sharing of household-maintenance tasks, engagement in joint activities, and trade-offs made by individuals between independent and joint discretionary activity participation. In addition to these inter-personal interactions, the intra-personal trade-offs among the different activity participation choices are also accommodated in this framework.

10.2.2 Flexible Discrete Continuous Models

The overall model system in this study comprises three components with the following econometric structures: (1) seemingly unrelated regressions, (2) joint mixed-logit hazard-duration structure, and (3) multiple (binary logit - linear regression) discrete-continuous system. The seemingly unrelated regressions model structure is well known in econometric literature. However, to our knowledge, this study represents the first applications of the other two structures (*i.e.,* the joint mixed-logit hazard–duration model and the multiple discrete-continuous model) for modeling discrete-continuous choices. Specifically, the joint mixed-logit hazard-duration model structure was used to model out-of-home maintenance activity participation choices and the multiple discrete-continuous system was used for modeling discretionary activity participation choices. Estimation of these flexible discrete-continuous models involves the use of simulation techniques to evaluate multi-dimensional integrals. For this purpose, this study used the Halton-sequence based Quasi Monte Carlo technique proposed by Bhat (2001a).

10.2.3 Algorithms for Disaggregate Predictions

This research also presents a micro-simulation framework for using the model system for predicting disaggregate, household-level activity-participation choices. Detailed algorithms were developed for using each of the three model components for predicting the corresponding activity-participation choices of the household adults. These individual component algorithms can be applied sequentially to completely determine all the maintenance and discretionary activity participation choices (both in-home and out-of-home) of household adults. These choices, in turn, can form inputs to detailed activity-schedule forecasting models and thus, be used determine the complete activity-travel patterns of each household adult. Thus, the overall model system developed in this dissertation, can be embedded as an enhanced "activity-generation module" within a comprehensive micro-simulation-based activity-travel forecasting system such as CEMDAP (Bhat *et al.*, 2004a).

10.3 Summary of Important Empirical Results

The three empirical models in this dissertation were estimated using data from the Bay Area Travel Survey, 2000. In addition, supplemental data on zonal demographics and land-use patterns and inter-zonal transportation level-of-service measures were also used. The important empirical results from the three model components are summarized here.

10.3.1 In-Home Maintenance Activity Generation Model

The models for in-home maintenance activity generation indicate that the daily time investments of the husband and wife in household chores are significantly impacted by individual/household characteristics and the daily mandatory activity participation characteristics of the household heads. In the case of households without children, the husband's out-of-home work duration determines the disparity between the time invested by the husband and the wife for household chores (*i.e.,* the longer the husband works out-of-home, greater is the difference in the in-home maintenance time investment of the household heads). In the case of households with children, the in-home maintenance time investments of both the husband and the wife are found to be negatively influenced by their respective work durations, but positively impacted by the work duration of their spouses. The commute duration was found to influence the in-home maintenance time allocation only for males in single-worker households. Finally, correlations between the male and female time investment models are positive indicating that common unobserved factors that increase the time investment of the wife in household chores, also increases the in-home maintenance duration of the husband.

10.3.2 Out-of-Home Maintenance Activity Generation Model

The empirical results for out-of-home maintenance activity generation indicate significant impacts of individual and household socio-demographic characteristics, mandatory activity participation characteristics, and in-home maintenance time investments on choices relating to undertaking of grocery shopping for the household. In general, the results indicate that grocery shopping during weekdays is most likely to be undertaken independently rather than jointly, possibly because of efficiency considerations achieved by task specialization. Joint grocery shopping is found to be motivated by resource constraints (*i.e.,* the non-availability of multiple vehicles in the household). Further, the model finds continued evidence for gender-based task allocations with women being generically more likely than men to undertake household's shopping.

The duration of work is found to negatively impact a person's propensity to undertake shopping, with this impact being stronger for women than men. With increasing women in the work force, this result suggests that more and more households may undertake grocery shopping on weekend days. Workers whose workday ends earlier are found to undertake shopping for longer durations. This effect must be accounted for in evaluating policy actions such as peak spreading by measures that release individuals early from work.

The model also indicates presence of significant positive correlations between the female's propensity to undertake shopping and her shopping duration hazard due to common unobserved factors. This suggests that, perhaps, women who are more likely to undertake shopping are also inherently more efficient shoppers.

10.3.3 Discretionary Activity Generation Model

The model for discretionary activity generation indicates the impact of several individual and household socio-demographic characteristics, and mandatory and maintenance activity choices on daily discretionary activity participation decisions of household adults. The availability of personal vehicle for each of the spouses is found to favor undertaking independent out-of-home discretionary activities. Adults in households with children (especially children of school-going age) are found to be less likely to engage in joint out-of-home activities.

Increasing daily time investments in work and in household chores is found to decrease the propensity to undertake discretionary activities during weekdays. Further, adults are found to be less likely to undertake out-of-home discretionary activities jointly, if one or both of them go to work. Thus, compressed workweek programs could result in increased possibilities of joint discretionary activities of the spouses on the day on which the adult does not have to go to work.

Adults who shop independently are found to be likely to undertake independent out-of-home discretionary activities and those who shop jointly are also found to prefer undertaking joint discretionary activities during the day. However, the time invested in shopping decreases the discretionary activity duration.

The daily discretionary activity participation choices of a person are also significantly influenced by the characteristics of the work and maintenance activities undertaken by his/her spouse. Thus, travel-demand management policy actions, such as flexible work hours, compressed workweeks, and home-based telecommuting. which influence the work duration of a person can also impact the in-home and out-of-home discretionary activity participation choices of the spouse resulting in changes to the overall travel patterns of *both* household adults.

The discretionary activity participation choices of the adults are also found to be impacted by common unobserved factors as indicated by the strong error correlations among the five discrete-continuous models. Specifically, common unobserved factors favoring in-home activity participation of the husband are also found to favor in-home activity participation of the wife. Similarly, unobserved factors positively influencing independent out-of-home discretionary activity participation of the husband also positively impact the corresponding choice of the wife. Further, the error correlations between in-home and out-of-home activity participation choices are negative, suggesting intra-personal and inter-personal substitution effects between independent in-home and out-of-home activity participation choices of the household adults. Finally, unobserved factors that increase the propensity for independent in-home activity participation also decrease the propensity for joint activity out-of-home participation.

10.4 Directions for Further Research

There are several avenues for further research in the area of activity-based analysis accommodating household interactions. Such further studies can substantially inform the development of operational, activity-based travel-demand forecasting systems that comprehensively model various intra-personal and inter-personal linkages the daily activity-travel choices. Some of the important research directions are presented here.

Use of more detailed descriptors of land-use patterns and transportation level-of-service characteristics as explanatory variables can further enrich the empirical specifications for the models presented in this dissertation. Such richer empirical specifications would be of particular value to practitioners, enabling the evaluation of the impacts of a wide array of institutional policy actions on the activity-travel patterns of the population.

This dissertation has focused only on the interactions between the *adults* in active, dual-adult households. It would also be useful to examine the interactions between adults and children, and also extended the overall scope of the analysis to retired households and larger households with three or more adults. As larger households have more interacting individuals, the linkages among the activity-travel patterns of the members in such large households may be more complex. At the same time, there may be fewer households with many adults compared to the number of smaller, nuclear-family-type households, thus limiting the availability of data for modeling the complex interactions. These considerations may require the development of appropriate modeling methods.

All the discussions above were in the context of future research in the area of modeling activity *generation*. As already identified in this dissertation, a subsequent step in the determination of the daily activity-travel patterns is activity *scheduling*. Clearly, there are also several linkages in the activity scheduling decisions of the different household members. An important area of future research is to model linkages in the scheduling decisions, in addition to modeling inter-personal interactions in activity generation, so as to completely describe the interdependencies among the activity-travel patterns of household members.

It is also necessary to examine household interaction patters over multi-day periods. Intuitively, one may expect the inter-personal linkages in the daily activity-travel patterns to be different for weekend days when compared to weekdays. Further, individuals also make trade-offs in activity-travel choices over mutli-day periods. Models based on single-day data implicitly assume behavioral independence in activity-travel decisions from day to day and hence cannot capture substitutions in activity patterns over periods longer than a day.

Research on modeling household interactions can benefit from additional data often not collected in conventional activity/travel surveys. For example, surveys do not clearly distinguish between activities undertaken by individuals for personal reasons from those that are undertaken to serve the household as a whole. This distinction is a key determinant of the nature of household interactions that shape the choices relating to this activity. Further, most travel surveys do not collect explicit information on joint activities undertaken by the household members. Similarly, for serve-passenger trips, information on the person being served and the activity undertaken by the served person are not available explicitly. The analyst is often forced to make assumptions in deriving such information. If such data could be collected directly, it could potentially reduce the errors that can be introduced by the data analysis procedures leading to deriving the necessary information. A very fruitful area of future research is therefore to explore data needs and develop activity-travel surveys that elicit the necessary information for modeling household interactions more efficiently.

Parallel to the research on *modeling* activity-travel patterns accommodating household interactions, efforts must also be invested in the development of methods for using these models for *forecasting*. Often, activity-based travel-demand modeling systems comprise a suite of interdependent models, and hence, forecasting activity-travel patterns is non trivial. A micro-simulation based approach may be very appropriate in this context. Further, activity-based forecasting is also a very data intensive exercise considering that the forecasting is performed at a disaggregate, household level. Transport modeling researchers need to sufficiently exploit the advances in the fields of database management and Geographic Information Systems (GIS) to efficiently handle and process the vast amounts of (non-spatial and spatial) data. In the overall, a micro-simulation based activity-travel forecasting software embedded within a GIS platform, can provide future transportation planners a very powerful tool for predicting travel patterns and undertaking realistic evaluations of the impact of policy actions toward achieving the goals of transportation and urban planning.

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